Intentional Self-Regulation and Self-Perceived Academic Success in Elementary School-Age Youth: A Relational Developmental Systems Approach

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Abstract

If society recognizes that it is mutually beneficial for individuals and communities to invest in school interventions that will lead to a more productive society, then early investment in intentional self-regulation (ISR) attributes may be a cost-beneficial strategy in regard to subsequent secondary-, post-secondary, and career successes, especially when early investment is complimented by continued investment in ISR through secondary school. In Chapter 1, I explain why ISR attributes should be a focus of educational curricula and interventions. I review several studies that have identified measures and tools that can be used to evaluate and improve ISR attributes among elementary school-aged youth, and how ISR attributes relate to academic success in elementary school students. In Chapter 2, I discuss the rationale for using longitudinal data from 959 participants in the Character and Merit Project (CAMP) to analyze the characteristics of ISR, as operationalized by Selection, Optimization, and Compensation (SOC) factors, and the outcome of interest, self-perceived academic success. I describe the findings of longitudinal analyses aimed at evaluating the utility of the Chase (2014) two-factor model of SOC, and how this two-factor model related to self-perceived academic success across the elementary school years. I used growth mixture models, cross-tabulation analyses, and tests of the equality of means to determine how SOC factors related to self-perceived academic success trajectory class membership. Chapter 3 explains the implications of the findings, as well as potential limitations. I conclude with a discussion of the possibilities for future studies of ISR and academic success, as well as the implications for educational policy and practice, within and after the elementary school years.

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Table of Contents

List of Tables

List of Figures

CHAPTER 1: METATHEORETICAL AND THEORETICAL BASES OF THE STUDY OF INTENTIONAL SELF-REGULATION

The purpose of this dissertation is to explore how intentional self-regulation (ISR) may relate to academic success. To rationalize the importance of this focus, I review relational developmental systems (RDS) metatheory, and discuss how this metatheory frames the study of ISR. I then discuss the state of academic success in the U.S., and how academic success relates to ISR. I next discuss measures of ISR, how these measures have been used to study the relations between ISR and academic success, and the implications of current and future research for applications in schools and youth development programs. Finally, I discuss the implications of potential findings for further research and academic interventions.

Introduction

The question of what makes a young person develop into a successful adult has been answered in many ways. Some ancient cultures stressed fate as the basis for success and, as such, were pessimistic about a person's ability to affect his or her own outcomes (Evelyn-White, 1914). For example, the ancient Greeks saw their life trajectories as largely out of their control, as predetermined by fate; the will of their gods (Evelyn-White, 1914). The word "fate," in fact, comes from the Greek term for three gods known as "the Fates" or the "Moirai" who determined the destinies of all mortal people (Raphals, 2002). The assumption that people are predestined for success or predestined for failure persisted for centuries, but has been nearly universally disregarded in the modern world (Raphals, 2002).

In the last century, the most prevalent understanding of what makes a person successful has involved a combination of influences of the environment on a person, and the characteristics and actions of the person within his or her environment (Reese & Overton, 1970). In

developmental science, early conceptualizations of the individual's relationship with the context were based on the nature-nurture controversy – a debate wrought from reductionist theories and dualisms, which emphasized either biology *or* experience as the key determinants of an individual's outcomes (Lerner, 2002). In contemporary developmental science, the Cartesian split between nature and nurture is seen as counterfactual, and both empirically and theoretically unproductive (Lerner, 2013; Moore, 2002; Overton, 2015). That is, today, nature and nurture variables are regarded as integrated parts of the multiple levels of organization comprising the ecology of human development; all variables within and across these multiple levels are conceptualized as parts of an inextricably fused developmental system (Lerner, 2013).

In other words, the reductionism that characterized split, nature-nurture, or simplistic interaction notions (e.g., Lerner, 1978; Overton, 2013) has been replaced with an understanding of developmental processes that is derived from RDS metatheory (Overton, 2013, 2015). The RDS metatheory postulates that developmental change is a consequence of the coaction of physiological (e.g., genetic, neuronal) variables and contextual variables that are fused across ontogeny; this fusion constitutes the fundamental, relational process that creates the structure and function of the organism (Gottlieb, 1992). RDS metatheory has gained currency in the study of human development, in part, due to its conceptualization of the mutually influential relations between agentic, developing individuals and an ever-changing context as the basic process of human development (Overton, 2013, 2015) and, in part, due to the elaborations of new methods to study the relational developmental system (Molenaar, Lerner, & Newell, 2014).

The relationism of RDS metatheory involves the concept of holism, that is, the idea that events are embedded within a context, and that events are a product of that relational context (Overton, 2013, 2015). From the relational perspective, parts and wholes are, necessarily,

inseparable (Overton & Lerner, 2014). In the RDS framework, individuals develop in physical, social, and cultural contexts in which individuals and contexts are mutually influential. Thus, individuals develop as co-acting parts of the system in which all levels of the ecology are fused (Overton, 2013, 2015). In addition, because RDS metatheory views all levels of the ecology as integrated, Overton (2015) explains that the development of individuals cannot be separated from their ecology across ontogeny.

Because this ecology involves history, or temporality, at its most macro instantiation, change, and the potential for systematic change, is a ubiquitous feature of the relational developmental system. The potential for such systematic change, for plasticity (Lerner, 1984, 2012), means that the mutually influential relations between individuals and contexts (relations labeled by Brandtstädter, 1998, as developmental regulations) possess, therefore, the possibility of change.

Of course, a system open to change may also be open to constraints on change (Lerner, 1984, 2013) and, therefore, plasticity is always relative to the particular features of the context within which the person is developing. Simply, development, and plasticity in development, varies in relation to time and place (Elder, 1998; Elder, Shanahan, & Jennings, 2015). As a consequence, plasticity varies intraindividually, across ontogeny, and interindividually, for each individual (Overton, 2013, 2015).

For example, a 73-year longitudinal study found that psychosocial growth as an adult may compensate for negative effects of an adversarial childhood with regard to adjustment to aging (Landes, Ardelt, Vaillant, & Waldinger, 2014). This study is an example of plasticity across ontogeny. Due to the diversity of experience, developmental level, and context, developmental science must, therefore, use change-sensitive methodologies to have a more

complete understanding of development (Overton & Lerner, 2014). Researchers in the field of *applied* developmental science may view the existence of relative plasticity as an opportunity for intervention, as experiences and contexts may be changed to influence subsequent individual outcomes (Overton & Lerner, 2014).

RDS Metatheory and ISR

As I have noted, RDS-based models stress that the basic process of human development involves bidirectional relations between the developing organism and a complex, changing context. Brandtstädter (1998) explained that, when these bidirectional relations, represented as individual ←→ context relations, are mutually beneficial, they may be termed *adaptive* developmental regulations. That is, the individual has characteristics that shape the structure and function of the context. At the same time, the context has characteristics that shape the structure and function of the individual (Brandtstädter, 1998).

The concept that a person may have a role in his or her own development was forwarded by researchers throughout the second half of the 20th century (Brandtstädter, 1998; Lerner, 1982). Theoretical approaches such as developmental contextualism, dynamic interactionism (Lerner, 2002), and the bioecological model of human development (Bronfenbrenner, 2005) have embraced this concept of bidirectional relations, and, therefore, have moved developmental science away from the idea that individuals are inevitably condemned to poor outcomes, or blessed with positive outcomes, based on the influences of their environment. Brandtstädter argued that contextualism and interactionism, although vastly improved from earlier conceptualizations, were still incomplete, because they:

> "…primarily conceived of development as the result of person-environment transactions rather than as a target area of intentional action; in other words, the relation between

action and development has been conceptualized primarily as a functional rather than an intentional one." (Brandtstädter, 1998, p. 535).

Brandtstädter argued that the omission of intentionality may be reasonable when considering development among infants and young children, who do not engage in contextual interactions with a fully developed sense of agency to further personal goals. Even actions that, upon observation, appear to be intentional, are often influenced by the goals and wishes of other individuals; usually the goals and wishes of the child's caregivers. Because caregivers generally determine the child's context and activities, they may largely dictate the child's development in co-constructive interactions within the greater context at early stages of development (Goodnow & Collins, 1990; Lerner, 1985).

Although intentions may not be as pronounced in the earliest stages of the life span, they do begin to emerge in early childhood as self-control strategies are acquired through socialization (McClelland, Geldhof, Cameron & Wanless, 2015; Mischel, Cantor, & Feldman, 1996). Such self-control strategies are, arguably, precursors to ISR (Brandtstädter, 1998), the ability to draw from individual and contextual resources to achieve one's goals (Gestsdóttir & Lerner, 2008). As individuals in their early lives gain greater autonomy, activities of ISR may become more salient, as they are applied to the individual's goals. Some of children's goals involve school-related activities, including, of course, academic tasks. Accordingly, the development of ISR in school-aged youth, and the relations of ISR attributes and academic success, will be the focus of this dissertation.

In this chapter, I begin by addressing three key issues related to academic success and ISR: 1. How might academic interventions that promote ISR contribute to academic success?; 2. Given RDS based, theory-predicated relations between ISR and academic success, can ISR be

identified among school-age youth, perhaps especially in the early years of school, when trajectories of development may be most important for later success (Heckman, 2008)?; and 3. If ISR in the early years can be assessed well, how may such measurement contribute to applications aimed at enhancing academic success? The need to address these issues will be underscored by an overview of the potential role of ISR in successful academic achievement among diverse children in the United States.

To address these issues, it is important to recognize that much of children's time and effort is spent in an academic setting. Decisions about how children spend their time are typically made for elementary school-aged youth by adults. However, in order to succeed in school, students must exhibit a degree of ISR (McClelland et al., 2014; McClelland et al., 2015). Whereas students' interests and goals are as diverse as the students themselves, the vast majority of long-term goals require some degree of academic success in order for the goal to be actualized (Ursache, Blair, & Raver, 2012). Even children who dream of becoming professional football players, for example, may improve their chances of success on the field by succeeding in high school, and attending a college where they may refine their football skills enough to become professionals. The majority of students, of course, will have more direct benefits from academic success, as most careers in the modern economy require a high school diploma, at minimum (Heckman & Masterov, 2007). Many researchers have argued that such academic success is as valuable for the community as a whole as it is for the individual who succeeds academically (e.g., Heckman & Masterov, 2007). I therefore begin with an overview of the state of academic success in the United States, and the implications of academic success and failure at individual and societal levels.

Academic Success in the Early School Years: An Overview

Although there are a wide variety of opinions on how we, as a society, should educate our youth, there is a virtually universal consensus that the education of youth is critically important to individuals seeking to lead productive, happy lives, and, in turn, to building stronger communities populated by competent individuals (Greenstone & Looney, 2011). The United States has enjoyed relative prosperity for much of its history (Freeman, 2006) but, in an age of globalization, there is a growing concern that the United States has lost some of its competitive advantage, and that its workforce is not fully equipped to compete in a modern, global economy (Freeman, 2006; Schneider & Yin, 2012).

In the last half century, an increasing percentage of careers require a college education, or specific technical degrees; yet, many students are unprepared, unable, or unwilling to attend college (Heckman, 2008). The United States invests a great deal of money in the education of its children, among the highest dollars-per-student in the world; and yet, our return on investment in the form of post-secondary educational attainment and gainful employment has been lagging behind many other countries in recent decades (Psacharopoulos & Patrinos, 2004).

One of the most commonly cited metrics of academic success in the United States has been national high school graduation rates (Heckman, 2008). However, pertinent data reflect a lack of success among diverse groups of U.S. youth (Heckman & LaFontaine, 2008). Men of all ethnic groups are currently graduating at a lower rate than they were in the mid-1960s (Heckman, 2008). In turn, women are 10% more likely to attend college than men (Goldin, Katz, & Kuziemko, 2006). Moreover, an increase in General Educational Development (GED) recipients, and a drop in high school graduation and college attendance, have led to stark forecasts for the near future. In addition, only 57% of students at public, four-year colleges

graduate within six years of entry (National Center for Education Statistics, 2010). With an increase in demand for skilled workers and a decreasing need for a low-skill workforce, this failure to produce college graduates represents a sizeable threat to the competitiveness of our economy, and the quality of life for young Americans (Schneider & Yin, 2012).

The reasons for the decline in graduation rate are assuredly complex, and hypotheses have varied. One suggestion points to slow decline of the American middle class, as manufacturing jobs, for example, once a staple of the economy in the United States, have become far less prevalent due to outsourcing and the increased use of robotics in manufacturing (Acemoglu, Dorn, Hanson, & Price, 2014; Foster & Wolfson, 1992). Alternatively, Moon (2008) suggested that a contributing factor to the lack of academic success is the rising percentage of single parents, who may have less time and resources to adequately care for, and provide for their children, than two-parent families. Indeed, there is a strong, positive correlation between single-parenthood and high school dropout (Moon, 2008).

Not all of the hypotheses regarding lack of school success are focused on deficiencies in individual students or their families, however; another hypothesis suggests that contextual factors, including attributes of students' schools, may be crucial for school success (Zaff, 2011). For example, 15% of high schools in the U.S. account for approximately 50% of students who drop out of high school (Balfanz, Bridgeland, Moore & Fox, 2010; Burrus & Roberts, 2012). Balfanz and colleagues (2010) labeled schools in which less than 60% of students graduate "Drop-out Factories." However, the term Drop-out Factory may be a misnomer, as it implies that the schools themselves are the primary cause of academic failure. We know that schools are only one possible contributing factor to the lack of academic success for students, as the vast

majority of the schools they attend serve cities and towns with extreme poverty, bringing with them a wide variety of social and structural challenges (Zaff, 2011).

In turn, in the face of a hypothesized lack of school success, some scholars have taken an implicit strength-based approach to the problem (e.g., Lerner, Lerner, Bowers & Geldhof, 2015). Rather than focus on the basis of failure, an emphasis has been placed on the attributes of youth and contexts that may be promoted or enhanced, respectively, to promote school success (Zaff, 2011). In other words, these scholars have taken, implicitly or explicitly, an approach to academic success consistent with RDS thinking (e.g., Lerner et al., 2015). They ask what attributes of youth and settings can be focused on, in order to optimize the chances for academic success in diverse youth (Lerner, Lerner, & Zaff, in press). One such attribute, intentional self-regulation, is discussed below.

1. How Might Promoting ISR Contribute to Academic Success?

Given the above assertion that a student's strengths may be optimized to promote success in school, a critical question is, what attributes of students may reflect potential strengths that, if promoted, can interrelate with their contexts to optimize their chances for academic success? Geldhof, Little, and Colombo (2010), Gestsdóttir and Lerner (2008), Heckman (2008), and McClelland and colleagues (2015) identified individual attributes related to self-control, self-governance, or ISR (in present terms) to be such characteristics. Consistent with RDS-based models of individual ←→ context relations linked with adaptive developmental functioning (Brandtstädter, 1998) in general, and with positive youth development outcomes such as academic success, more specifically (Lerner et al., 2015), ISR is the person component of individuals' exchanges with their contexts, such as formal educational settings, that may enable

successful navigation of school requirements (McClelland et al., 2015), fostering academic success across subsequent ontogenetic periods (Heckman, 2008).

For instance, early educational interventions that promote the development of self-regulatory abilities may play an equally important role in early academic and later career success (Heckman & Masterov, 2007). Examples of such attributes include conscientiousness, farsightedness, persistence, and emotion control (Heckman & Masterov, 2007). ISR attributes are even more predictive of graduation from college (for males, in particular) than traditional academic abilities such as reading and writing (Heckman, Stixrud, & Urzua, 2006). Thus, interventions designed to increase ISR attributes in early childhood seem to foster abilities that lead to later academic success, and that may counter cycles of inequality.

In addition to the benefits experienced by the individual, early intervention involving promoting ISR has been shown to boost productivity in the economy. One key contribution by Heckman and colleagues (2006) has been the econometric techniques brought to bear on the complex phenomena of parental investment and, as well, community investment in the development of a child. These methods take into account both the importance of early investment and the financial consequences that are incurred as a result of non-investment. Heckman and colleagues (2006) demonstrated that parental “investment choices” (in regard to time, activity participation, and school choice) predict outcomes of their children in a wide range of dimensions. For example, taking into account the concept of preference formation, such as the development of a preference for (or against) high-risk activities, can explain the success of many early childhood programs for disadvantaged children. These programs may fail to predict long-term increases in traditional measures of intelligence, such as IQ scores. However, the

participants in the program demonstrated greater, sustained ISR attributes (Heckman et al., 2006).

By implementing curricula that promote attributes such as persistence and farsightedness in early intervention programs, youth may actually improve their self-regulatory abilities, not just their IQ. Even after IQ effects of a program may wear off, the ISR characteristics remained, and demonstrated a strong, negative association with participation in high-risk activities, such as smoking (Heckman, 2008). These results are consistent as well with the later-life advantages among those children who showed greater self-control and resistance to temptation in the famous "marshmallow" experiment, in which young children who displayed the ability to delay gratification were more likely to become cognitively and socially competent as adolescents, and achieve greater school success (Mischel, Shoda, & Rodriguez, 1989).

Of course, ISR is not the only predictor of academic success. Heckman's (2008) model took into account other aspects of early investment in youth development, such as physical health and more traditional academic education during early childhood and adolescence. Using econometric analysis, Heckman reported that subsequent adult successes were strongly predicted by early childhood indicators. That is, if a youth lived in a low resource environment, and early community investment in these youth was minimal, low levels of early investment could not, in most cases, be easily remediated or replaced by later investment in adolescent development. Conversely, in a low resource environment, if early investment in a youth was high, and if this investment was followed up with moderate-to-high later investment, the effects of early investment were sustained. Predictably, the best developmental outcomes were found in youth who receive high initial family investment, along with high early life and adolescent community

investment (Heckman, 2008). In short, early and sustained investment in youth, by their family and their community, was the most predictive of academic success, and other positive outcomes.

This econometric research demonstrates what Heckman and colleagues (2001) called a capability multiplier, which explained why societal, economic returns on self-regulatory and academic education are relatively lower in the adolescent years for youth in low resource environments, but returns on investment are high in the early years (Heckman, Hsee, & Rubinstein, 2001). As such, if ISR attributes can be validly marked in the early school years, interventions focused on such attributes may be enhanced. Programs that focus on ISR and features of the school setting that may sustain or enhance ISR functioning, or in other words, improve the quality of individual ←→ context relations, may stand a better chance of promoting academic success. That is, if youth do not receive strong foundations for later learning, adolescent interventions will have lower "returns-on-investment," as youth are less likely to be prepared to capitalize on later investments (Gluckman & Hanson, 2005).

There are several early educational interventions that include the inculcation on self-regulation skills as a key aspect of program design. One such early education program, Tools of the Mind, focuses on developing self-regulatory attributes in early education settings to prepare students to succeed academically as they enter elementary school. Tools of the Mind is both a prekindergarten curriculum and a professional development program for prekindergarten teachers. Teachers in the Tools of the Mind program use Vygotskian scaffolding and modeling techniques to help students develop what the program terms "learning-related self-regulation" (Wilson & Farran, 2012).

A related program that includes ISR as a program goal is called Evidence-Based Program for Integrated Curricula (EPIC; Fantuzzo, Gadsden, & McDermott, 2011). EPIC's integrated

curricular approach includes traditional learning modules for mathematics, language, and reading skills; however, EPIC also emphasizes self-regulation skills applicable to school success, such as task approach (i.e., developing and practicing creative problem solving skills, and planning toward goals). EPIC also encourages executive function skills such as attention control (i.e., skills related to focus and persistence toward completing a task; Fantuzzo, et al., 2011).

The EPIC and Tools of the Mind curricula have shown promising results as early education interventions that yield academic benefits for students, presumably as a result of their emphasis on the development of ISR attributes (Fantuzzo, Gadsden, & McDermott, 2008, 2011). Indeed, early education research has linked Specific Approaches to Learning (SAL), a teacher reported measure defined by task-orientation (i.e., attention, motivation, persistent effort, and attitude), to subsequent kindergarten and first grade academic success. Therefore, student participation in curricula that emphasize ISR attributes in the school context positively relates to academic performance in elementary school (McWayne, Green, & Fantuzzo, 2009).

Similar school programs encourage self-regulation attributes through the framework of Social Emotional Learning (SEL), a construct which includes many of the same goals as intentional-self regulation interventions, including setting positive goals, and emotion regulation (Elias, 2004). A meta-analysis of SEL interventions showed that SEL attributes can be taught in classrooms, and that these SEL attributes related to school success (Durlak, Weissberg, Dymnicki, Taylor, & Schellinger, 2011).

Another related concept that has implications for teaching methods and educational policy is the growth mindset perspective. This perspective, explained in greater detail in Chapter 3, is based on encouraging and rewarding attitudes and behaviors that show a student's willingness to work hard toward academic goals, as opposed to reliance on a perceived level of

so-called innate talents, characterized as a fixed mindset (Dweck, 1999). Dweck (2006) contrasted the growth mindset classroom approach with the fixed mindset classroom approach, and found that students in classrooms that promoted a growth mindset had greater academic outcomes than students in the fixed mindset classrooms. Therefore, students who felt hopeful and empowered to work toward their academic goals, under the assumption that their efforts would be rewarded, were more successful in school.

The notion that a positive outlook relates to academic and other success can be expanded to a long-term outcome mindset as well. A youth's hopeful future expectations (i.e., perception of positive outcomes as adults, including family and career outcomes) relate positively to thriving outcomes (Schmid, Phelps, & Lerner, 2011). It is possible, then, that students need to both possess ISR attributes that contribute to academic success, and expect that their futures will be positively impacted by their efforts in school, such that they perceive a strong "return on investment" for their efforts in the academic context (see Dweck's, 2006, rationale for studying fixed versus growth mind-sets, for an example of similar reasoning).

In sum, based on the findings I have reviewed, a key implication for educational policy is that sustained, early interventions that promote ISR and related concepts should be present in schools and, arguably, especially schools in high-risk communities in the United States, if academic success is to be optimized. To maximize their effectiveness in enhancing academic success, such interventions should be targeted toward students in communities with "drop-out factories" (Balfanz et al., 2010) and for students who exhibit early warning signs for school drop-out (Burrus & Roberts, 2012). A goal of the current investigation was to determine when and how ISR attributes may provide students with the greatest benefits to their academic success.

2. Can ISR be Validly Assessed Among Elementary School-Aged Youth?

In order to undertake effective interventions such as those described above, definitions, descriptions, and evaluations of ISR in young students are needed. However, ISR is just beginning to be studied and evaluated among youth of these age levels. Researchers from several disciplines have attempted to measure attributes that fall under the umbrella of ISR (e.g., Duckworth, Peterson, Matthews, & Kelly, 2007; Geldhof et al., 2014; Gestsdóttir & Lerner, 2008; Heckman et al., 2006). It is encouraging that scholars from different academic fields have explored various aspects of self-regulation, but the presence of so many definitions and measures creates complicated choices regarding how to operationalize ISR. For example, related definitions and measures have come in the form of executive functioning (studied in the main by cognitive and neuroscience researchers, e.g., through use of the EPIC and Tools of the Mind curricula; Fantuzzo, Gadsden, & McDermott, 2011), intentional self-regulation (assessed by developmental researchers), and the Approaches to Learning concept (studied by early childhood researchers). Because, in current scholarship in developmental science, several researchers have conceptualized ISR through the lens of RDS metatheory, it may be most useful to define ISR as a characteristic that links the individual to resources in their context that are associated with positive development (Gestsdóttir & Lerner, 2008; Geldhof, Little, & Colombo, 2010; McClelland et al., 2015).

These ideas have been instantiated in at least two somewhat related ways. One instantiation focuses on various substantive domains of self-regulatory processes, such as grit, characterized by perseverance and passion for one’s goals (Duckworth et al., 2007), or emotion regulation, which can be defined as controlling one’s thoughts, actions, and interactions despite emotion arousal (Denham, 2006; Raver, 2002). A second instantiation of the link between ISR

processes and positive developmental outcomes documents the presence and role of behavioral, emotional, and cognitive ISR processes at different points in the life span (e.g., McClelland, Cameron-Ponitz, Messersmith, & Tominey, 2010; McClelland et al., 2014).

McClelland and colleagues (2010) operationalized ISR using behavioral indicators in the classroom context. In the preschool age group, behaviors were used to index executive function processes such as inhibitory control (i.e., fighting a dominant response in place of an adaptive response), working memory (i.e., keeping information in one's mind), and attentional flexibility (i.e., keeping one's focus despite changing goals) (Dowsett & Livesey, 2000; Rueda, Posner, & Rothbart, 2005). ISR was defined as the behavioral manifestation of these three executive functions, as indexed in the Head-Toes-Knees-Shoulders (HTKS) task (McClelland et al., 2014), an assessment that involves individual testing of children by trained researchers. These behavioral tests of attention and cognitive flexibility were considered particularly relevant for school-aged children who had to learn to focus, ignore distractions, and sustain attention on tasks in the classroom (Rothbart & Posner, 2005).

Another operationalization of ISR involved the Baltes and Baltes Selection, Optimization, and Compensation (SOC) model, which was originally used in adulthood and has since been modified for use in adolescence (Baltes & Baltes, 1990; Freund & Baltes, 2000, 2002; Gestsdóttir & Lerner, 2007) and childhood (Hilliard et al., in press; Wang et al., in press). In the SOC model, self-regulation involves goal selection, goal optimization by managing one's resources, and compensatory strategies for use when optimization strategies fail at first or are blocked. Therefore, important ISR-relevant strengths involve elective selection (S), optimization (O), and compensation (C) – strengths that enable the individual to draw from contextual resources needed for positive development and, at the same time, contribute to his or

her context (Gestsdóttir, Lewin-Bizan, von Eye, Lerner, & Lerner., 2009; Gestsdóttir & Lerner, 2007).

This SOC model was used in the 4-H Study of Positive Youth Development (PYD) to measure ISR in the second decade of life (Lerner et al., 2005). Some of the youngest participants were evaluated with a self-report SOC scale at the beginning of the 4-H Study of PYD, wherein Grade 5 participants were surveyed (Lerner et al., 2005). Various studies using the 4-H data set established that, instead of a construct differentiated into three sub-constructs (Selection, Optimization, and Compensation), as had been found in adult populations, younger participants (10 to 13 year-olds) demonstrated a global SOC structure which manifested itself in a single, undifferentiated SOC factor (Gestsdóttir & Lerner, 2007; Gestsdóttir et al., 2009). Among participants who participated later in the 4-H Study (14 to 18 year-olds), Selection, Optimization and Compensation began to demonstrate differentiation, represented in a three-factor solution. However, evidence of a strong tripartite solution across studies was inconclusive (Geldhof et al., 2014).

The SOC measure is useful in studies involving testing large groups of youth, as often occurs in survey research such as the 4-H Study of PYD. However, the efficacy of such a measure has often been unavailable in studies involving younger children where, until recently (Chase, 2014) only the individually administered HTKS index was available. Such use of a group-administered index of ISR would be particularly useful, however, given issues of research efficiency, cost, and the substantive point that elementary school aged youth may be an important age group for determining trajectories of SOC skills, and subsequently, academic success (Heckman et al., 2001; Balfanz, Herzog, & MacIver, 2007).

Progress in the development of such a measure exists. Data from the Character and Merit Project (CAMP) Study (Hilliard et al., in press) include six items based on the SOC model, and this item set allowed such a group-administered measure to be developed in a psychometrically sound way. The CAMP study is an investigation designed to measure the development of character in Cub Scouts. A six-item version of the SOC measure used previously with adolescents was modified, and administered to elementary school-aged participants. Chase (2014) assessed whether this instantiation of the SOC measure used in the CAMP study provided a reliable, psychometrically-sound measure, sufficient for studying ISR at the elementary school age-level. Using exploratory and longitudinal confirmatory factor analysis from four waves of the CAMP study, Chase found a two-factor model of SOC that divided items into two components – individually-oriented SOC, and other-oriented SOC – for elementary school-aged boys. Chase (2014) interpreted the two-factor solution as an operationalization of concepts of RDS metatheory, for example, embodiment in a social world (Overton, 2015), which may involve looking to others for help to achieve one's goal, and agency (Sokol, Hammond, Kuebli, & Sweetman, 2015); that is, working as an individual to achieve one's goal.

In addition to a SOC measure, the CAMP study included a measure of self-perceived academic success (i.e., the participant's perceptions of his or her academic ability, formed through experience). Chase (2014) found that both SOC factors were related to self-perceived academic success among elementary school-aged boys. However, the individually-oriented SOC factor was more highly correlated with self-perceived academic success than the other-oriented SOC factor.

No causal conclusions could be drawn from the Chase (2014) findings; however, the findings suggested several opportunities for further research, such as exploring how these two

SOC factors may relate to self-perceived academic success longitudinally. Indeed, I chose to explore the longitudinal relations between SOC factors and self-perceived academic success among elementary school aged youth as the focus of this investigation. In the following section, I present examples of how measurement of SOC in youth may be improved, and subsequently used to improve academic success outcomes.

3. How Might ISR Measurement Contribute to Applications Aimed at Enhancing Academic Success?

In this section, I discuss the potential opportunities for, and benefits of, a valid measurement tool for evaluating ISR in elementary school-aged youth. As reported above, Chase (2014) found a two-factor model of SOC that divided SOC into individually-oriented SOC items, and other-oriented SOC items for elementary school-aged boys. With this two-factor model of SOC in mind, I offer here an in-school example that illustrates how SOC-based evaluation tools may be useful for teachers whose curricula call upon different instantiations of ISR at different developmental levels, such that individual- and other-oriented SOC may be a priority for students in different elementary school grades. Thus, evaluation and intervention could be targeted to improve relevant ISR attributes in school settings.

However, schools are not the only settings in which SOC attributes and subsequent academic outcomes may be improved. In fact, several out-of-school-time (OST) programs have piloted an operationalization of SOC in the form of evaluation rubrics. These rubrics have been used to measure and enhance ISR in previous studies, such as Project GPS (Bowers, Wang, Tirrell, & Lerner, in press; Napolitano et al., 2014). The possibilities for in-school and OST applications of the SOC model for developing ISR and, therefore, for creating a greater likelihood for academic success, are described below.

Applying the SOC model of ISR in Schools

If the two-factor model of SOC (Chase, 2014) is used by educators to evaluate ISR in young elementary school students, this operationalization could inform teachers' understanding of the different ways in which intentional self-regulatory processes may relate to self-perceived academic success. Educators recognize that different study skills become important at different stages of a student's academic career. Montague (2007) found that, in early elementary grades, classwork typically can be learned one skill at a time through memorization, without requiring students to constantly call upon previously learned concepts. When recall of previous skills is required, students are typically only expected to demonstrate shallow, basic understanding of these skills (Montague, 2007).

One possible explanation is that this quickly-changing, teacher-directed learning asks less of students with regard to individual-oriented SOC, as the planning and evaluation of instruction are clearly under the aegis of the teacher, and little student-based initiative is expected. For example, reading and writing skills are a top academic priority across the United States throughout the elementary school years. In the *early* elementary school grades, students are primarily "learning to read," which requires that students demonstrate some basic antecedents of ISR, such as attentional flexibility and inhibitory control (McClelland et al., 2015). However, by *later* elementary school, students are typically asked to shift from "learning to read" to "reading to learn" (Chall & Jacobs, 2003; Chall, Jacobs, & Baldwin, 2009). Therefore, because students are asked to build on and apply their reading skills, Grade 4 may be a point when new and different skill sets, including ISR, become critical to academic success. Eccles and Midgley (1989) observed a similar shift as students struggled to adapt to changes in expectations from year to year, and from teacher to teacher. The Eccles and Midgley (1989) study exemplifies how

transitions across grades can include changes in expectations, and a student's ability to adapt to such shifts in expectations may predict academic success.

Some of these new skills required for youth as they move through elementary school may be components of the individually-oriented SOC component of ISR (e.g., planning and self-evaluation), components that develop throughout the elementary school years (McClelland et al., 2015). ISR contributes to many aspects of learning by helping students to maintain control of their actions and to learn independently (Blair & Razza, 2007), such as, when working alone and encountering a problem that cannot be solved alone, asking for help from teachers (a demonstration of other-oriented SOC). Students can also demonstrate ISR by simply recording whether they have remained on task, or through "showing their work."

These independent learning tasks in school are called self-instruction, which can be defined as the ability of a student to plan, develop, direct, and evaluate his or her own independent learning without a teacher's prompting or assistance (Wehmeyer, Agran, & Hughes, 2000). A meta-analysis conducted by Kroesbergen and Van Luit (2003) found that self-instruction, which requires substantial ISR-related characteristics (e.g., planning, self-evaluation and inhibitory control; McClelland et al., 2015), is the most effective method for teaching problem-solving in math classes. That is, youth who work through the problems themselves demonstrate better mathematics skills when tested on problem-solving ability. However, direct instruction by the teacher was found to be the most effective when teaching *basic* math skills (Kroesbergen & Van Luit, 2003).

Based on the above findings regarding reading and mathematics instruction, I postulated that different aspects of ISR would be more related to academic success at different grade levels. This idea led me to test whether both other-oriented and individual-oriented SOC contributed to

academic success, with the expectation that other-oriented SOC would play a larger role in early elementary school (i.e., attributes that assist in direct teacher instruction), and individually-oriented SOC would be more relevant in late elementary school and beyond (i.e., attributes that may assist in self-instruction). The analyses I conducted to test this idea are explained in Chapter 2.

The SOC Model of ISR in Out-of-School-Time Programs

In-school settings may be a promising context for the evaluation of and intervention in ISR development. However, several studies have begun to evaluate SOC in elementary school aged youth in relation to their participation in OST programs. For example, data from the CAMP study suggest that Cub Scout participation may positively influence character and other positive outcomes in boys, including school success (Hilliard et al., in press). Zaff (2011) has underscored the connections between in-school and OST activities, and therefore the idea that academic success is not only a product of in-school curricular innovations (see too Vandell, Larson, Mahoney, & Watts, 2015).

Lerner (2004) notes that OST programs that effectively promote positive outcomes such as academic success and PYD have three fundamental characteristics, termed the “Big 3:” 1. Positive and sustained adult-youth relations; 2. Life-skill building activities; and 3. Opportunities for youth participation in and leadership of valued family, school, and community activities. Although Scouting does not explicitly refer to the “Big 3” in its program, the presence of the “Big 3” has been identified as a key aspect of Scouting (Hershberg, Chase, Champine, Hilliard, & Lerner, under review; Hilliard et al., in press). Therefore, the CAMP study sought to determine whether Scouting participation is associated with positive outcomes, including

academic success. In the current study, I tested the notion that Cub Scout participation may relate to academic success and ISR. These findings are presented in Chapter 2.

GPS Study findings

Scouting, however, is only one of many potential OST contexts for implementing interventions that promote ISR in youth so that, in turn, enhanced ISR may impact the academic outcomes of youth. Participation in any of a variety of high quality OST programs predicts positive outcomes, including academic success (Vandell et al., 2015: Zaff, Moore, Papillo, & Williams, 2003) and PYD (Balsano, Phelps, Theokas, Lerner, & Lerner, 2009). OST programs that include mentoring may offer additional benefits to the development of ISR (Rhodes & Dubois, 2008). For example, youth-serving organizations that focus on youth mentoring may encourage youth to identify and pursue meaningful goals, and develop persistence toward those goals (Larson, 2000; Watts & Caldwell, 2008). Therefore, OST mentoring programs may be a useful setting within which to develop ISR in youth.

Project GPS (Bowers et al., in press; Napolitano et al., 2014) was a study of mentor-mentee pairs in OST programs. Mentors often teach and act as role models in contexts salient to youth. As such, youth relationships with mentors may serve as contextual resources that promote youth strengths, including ISR. Therefore, in order to facilitate, as well as improve understanding of mentoring programs, Project GPS was designed to develop and evaluate tools to help mentors promote ISR skills in their mentees.

The GPS project used the metaphor of a car's GPS navigation system – in which mentees "choose your destination" and the GPS components (SOC attributes in the case of this project) provide "strategies" to arrive at a mentee's destination (in this case, at achieving a goal) (Napolitano et al., 2014). In Project GPS, "G" stands for "Goal Selection," (Selection); "P"

stands for “Pursuit of Strategies,” (Optimization); and “S” stands for “Shifting Gears,” (Compensation). Project GPS included a set of tools for mentors that was designed to be adaptable to nearly any type of youth development program as a supplement to their standard mentoring practices (Napolitano et al., 2014). The first of these tools was a set of GPS rubrics, designed to evaluate and explain the importance of SOC strategies to youth. In addition, mentors could choose from a series of hands-on activities to practice and explain how to successfully pursue goals using the SOC (GPS) strategies. Finally, a series of exemplar videos featuring youth who demonstrated exceptional goal pursuit strategies was also available (Napolitano et al., 2014).

To determine whether the GPS tools were effective in promoting SOC strategies, the GPS project evaluated rubrics that included both self-reported and mentor-reported assessments of the mentees’ GPS attributes (i.e., scores on the rubrics). These GPS rubrics were adapted from Baltes and colleagues SOC model (e.g., Freund & Baltes, 2002). With data from these rubrics, Napolitano and colleagues (2014) found that, over three occasions of measurement, SOC could be measured by a single, global SOC factor for both older (14 to 18 year-old) and younger (eight to 13 year-old) mentees. Older mentee and mentor data were invariant across occasions of measurement and rater, whereas younger mentee and mentor data were invariant across occasions of measurement (Napolitano et al., 2014).

Notably, all mentoring programs that participated in Project GPS were selected, in part, because they fit the definition of effective youth development programs; that is, these mentoring programs included the “Big 3” of successful OST programs, as discussed above (Lerner, 2004). A study involving data from the GPS Project found that the quality and strength of the mentor-mentee relationship positively predicted growth in a latent factor of youth ISR (Bowers et al., in

press), thus confirming the assertion by Lerner (2004) that sustained, positive mentoring, part of the "Big 3," was indeed associated with positive outcomes among program participants, including ISR attributes.

Although participation in OST mentoring programs had been shown to predict ISR, such programs have not typically sought to teach ISR explicitly (Gestsdóttir et al., 2014). Mentoring relationships were ideal for a study of teaching ISR strategies (especially goal pursuit strategies) because the focus of mentoring programs is often on a long-term task of interest to the youth (Rhodes & DuBois, 2008). This focus allows mentors to help their mentees to pursue personally meaningful activities and goals.

In sum, the above studies are examples of how ISR measurement tools can be developed and implemented in both in-school and OST settings. ISR evaluation tools such as SOC could, therefore, be used in schools to improve assessment and intervention techniques for elementary school students. Improvements in assessment and intervention have already been made in studies involving OST programs such as BSA (Hilliard et al., in press), and Project GPS mentoring programs (Napolitano et al., 2014).

As applied developmental researchers continue to develop and refine these RDS metatheory-predicated evaluation tools, these measures and interventions may be used to help students navigate their contexts more efficiently, develop goal pursuit strategies and, in turn, apply their own, individually- and other-oriented SOC attributes toward long term goals. This optimistic view leads to some final points pertinent to the research focus of this dissertation.

Summary

From the RDS metatheory perspective, researchers have focused on an aspect of the individual's contribution to adaptive developmental regulation, ISR (Brandtstädter, 1998).

Intentionality may not be fully developed in the earliest stages of the life span, but self-control strategies (precursors to ISR) do begin to emerge in early childhood (McClelland, Geldhof, Cameron & Wanless, 2015). In later childhood, ISR, the ability to draw from individual and contextual resources to achieve one's goals, may develop (Gestsdóttir & Lerner, 2007; Gestsdóttir et al., 2009). Accordingly, I have discussed how ISR relates to an individual's goal pursuit, as well as the pursuit of academic success.

To elucidate this relation, I addressed three issues. In regard to Issue 1, "How might academic interventions that promote ISR contribute to academic success?," the evidence I reviewed leads to the conclusion that ISR may contribute to thriving outcomes, including academic success (Lerner et al., 2015). Further evidence suggested that it was equally important to invest in ISR attributes for academic, and eventual economic success, both at the individual and community levels (Heckman et al., 2001), and that these investments in ISR showed the greatest benefits in early education, complimented by continued cognitive and self-regulatory support through elementary and middle school (Heckman, 2008).

In regard to Issue 2, "Given RDS based, theory-predicated relations between ISR and academic success, can ISR be identified among school-age youth, perhaps especially in the early years of school, when trajectories of development may be most important for later success?," the evidence indicated that, a measure informed by and framed within RDS metatheory (Overton, 2013, 2015), and derived from the SOC model (Baltes & Baltes, 1990; Freund & Baltes, 2000, 2002), demonstrated validity and reliability among the target population of elementary school-aged youth (Hilliard et al., in press; Wang et al., in press). The adapted SOC measure used in the CAMP study (Hilliard et al., in press) also demonstrated construct validity through its correlation

with a key outcome variable, self-perceived academic success (Chase, 2014). Thus, SOC was a potentially useful tool for measuring ISR in elementary school-aged youth.

In regard to Issue 3, "If ISR in the early years can be assessed well, how may such measurement contribute to applications enhancing academic success?," studies of BSA and the GPS Project mentoring tools suggested how in-school SOC may be improved, and the connection between in-school and OST "learning," enhanced. Thus, the development of valid measures and tools related to ISR can be used to both evaluate and improve interventions that may, if effectively implemented, contribute to academic success.

Together, then, the discussion of these three issues provided a rationale for the empirical issues addressed in this dissertation: that is, my work evaluated the two-factor (individually- and other-oriented) model of SOC among elementary school-aged youth (Chase, 2014). I conducted a series of longitudinal analyses to determine whether individually- and other-oriented SOC predicted self-perceived academic success differently across grades in school. Accordingly, in Chapter 2 I explain how the goals of this dissertation were addressed using the data set and analytic methods that I employed. In Chapter 3, I discuss how the findings may be interpreted in regard to adaptive developmental regulations in the school context.

CHAPTER 2: METHOD AND RESULTS

Considerable research has focused on the individual's role in adaptive developmental regulation and, as discussed in Chapter 1, the individual's role may be specified through the Baltes SOC model of ISR (Baltes & Baltes, 1990; Freund & Baltes, 2000, 2002). Baltes and colleagues' SOC model was adapted for use in the 4-H Study of PYD to measure ISR in the second decade of life (Lerner et al., 2005). Various studies using the 4-H data set established that, instead of a construct differentiated into three sub-constructs (Selection, Optimization, and Compensation), as had been found in adult populations, younger participants (10 to 13 year-olds) demonstrated a global SOC structure which manifested itself in a single, undifferentiated SOC factor (Gestsdóttir & Lerner, 2007; Gestsdóttir et al., 2009). Among participants who participated later in the 4-H Study (14 to 18 year-olds), Selection, Optimization and Compensation began to demonstrate differentiation, represented in a three-factor solution. However, evidence of a strong tripartite solution across studies was inconclusive (Geldhof et al., 2014).

One gap in this life-span assessment of measures, particularly in regard to the use of SOC, has been in the early elementary school grades, which is the focus of this dissertation. Data from the Character and Merit Project (CAMP) study (Hilliard et al., in press) included six items based on the SOC model, and may allow this gap to be filled. In the CAMP study, an investigation designed to measure the development of character and other key outcomes in Cub Scouts, a version of the SOC measure used previously with adolescents was modified, and administered to elementary school-aged participants. Chase (2014) found that the instantiation of the SOC measure used in the CAMP study provided a reliable, psychometrically-sound measure, one sufficient for studying ISR among elementary school-aged participants.

Specifically, Chase (2014) found a two-factor structure, and that these two SOC factors, individually-oriented SOC (ISOC), and other-oriented SOC (OSOC), were invariant across the first four waves of measurement in the CAMP study. In addition, self-perceived academic success was found to be positively related to both SOC factors. However, within the overall CAMP study sample, the relations were stronger between ISOC and self-perceived academic success, as compared with OSOC and self-perceived academic success.

This contrast raised a series of research questions which became a focus of this dissertation. These research questions began with tests of invariance of the academic success, ISOC, and OSOC factors across grade in school in the CAMP study data set. Invariance testing was followed by a series of analyses to determine the latent trajectory (or trajectories) of self-perceived academic success. I then determined how OSOC, ISOC, and other factors (including Cub Scout participation) predicted the self-perceived academic success trajectories. The design of the CAMP study, participants, measures, procedures, and plan of analysis are described below.

Method

Design of the CAMP Study

This dissertation used a data set that was part of a longitudinal and mixed-method collaborative assessment of the impact of the Boy Scouts of America (BSA) program on youth character development: the Character and Merit Project (CAMP) (Hilliard et al., in press). Specifically, the CAMP study was a partnership with BSA leadership in the greater Philadelphia area, primarily designed to assess whether BSA participation positively influences character and other positive outcomes (such as academic success) in boys. Participant recruitment involved sampling both Scout and non-Scout groups with a series of questionnaires sent every six months

over the course of 2.5 years. Five waves of data were collected. In addition, there was a series of interviews with Scout leaders and youth, but these interviews were not used in this dissertation.

Measures

SOC. To measure ISR, the CAMP study included a six-item Likert-type version of the SOC scale (SOC; Baltes & Baltes, 1990; Freund & Baltes, 2002), adapted from 4-H Study of PYD (Gestsdóttir & Lerner, 2007). The original version of the SOC scale was in a forced-choice format, asking participants to read two statements and to choose which statement best reflected their behavior. For example, participants were asked to choose if they were more similar to 'Person A', who says "*I am always working on several goals at once*" or 'Person B' who says "*I always focus on the one most important goal at a given time.*" In the forced choice format, Person A and Person B demonstrated SOC or lack of SOC attributes. The CAMP study, however, used a Likert-type format, which has been established as having similar psychometric properties to the forced-choice format, but with the advantage of providing the opportunity for more response variation (Geldhof et al., 2014).

SOC items used in the CAMP study were adapted to be comprehensible for even the youngest of participants, who were in Grade 1 (i.e., as young as six years old). The six Likert-type items were divided into the two-factor model identified by Chase (2014). This division included two items for the OSOC factor: *"1. I can ask for help from others,"* and *"2. When I am having trouble, I ask for help,"* and four items for the ISOC factor: *"1. I am good at making plans,"* "*2. I am a hard worker*," *"3. When I want something, I try different ways to get it,"* and *"4. When I am having trouble, I think of new ideas."* In the CAMP study, participants were presented with these SOC-related items and were asked, "Is this like you?" Participants circled a

number on a scale of 1-5, from 1 "*Not at all like me*" to 5 "*Exactly like me*." These SOC factors, although not yet differentiated into the traditional tripartite model of Selection, Optimization, and Compensation, can still be considered a part of the SOC framework, with the expectation that the two-factor model will differentiate into a tripartite model in adolescence.

Previous findings using data from the 4-H Study of Positive Youth Development (PYD) suggested that, at Grade 5, global SOC scores would be quite high (see Bowers et al., 2011). The CAMP study measures of ISOC and OSOC were adapted from measures used in the 4-H Study of PYD. Therefore, when observing ISOC and OSOC trajectories from Grades 2 through 5 of the CAMP study, I expected the majority of participants to be either relatively high and stable, or increasing to high in ISOC and OSOC across elementary school by Grade 5.

Self-Perceived Academic Success. A measure of self-perceived academic success was included in the CAMP study as an index of academic success. The scale includes three Likert-type items, simplified and adapted from the academic competence subscale of the Self-perception Profile for Children (SPPC: Harter, 1982). The items were phrased as follows: *"1. I am very good at my schoolwork," "2. I can figure out the answers in school,"* and *"3. I get good grades in school."* Another item, *"I think schoolwork is hard"* (a reverse-coded item) was not included in the current analysis because preliminary analysis showed that it lowered the reliability of scores on the scale to an unacceptable level among male longitudinal participants in the CAMP study.

Previous studies (e.g., Chase, Hilliard, Geldhof, Warren, & Lerner, 2014) used self-reported grade point average (GPA) as a measure of academic success in secondary school students. The CAMP study used items based on self-perceptions of academic success instead of GPA. GPA does not exist in most elementary schools, and performance is not as simple to

quantify due to myriad ways of measuring academic success in elementary school classrooms. Therefore, the CAMP study's index of academic success, self-perceived academic success, is based on participants' perceptions of their success in school; perceptions presumed to be based on their experiences, which are sufficiently related to actual experiences that self-perceived academic success is considered a reasonable proxy for grades (Anderman & Midgley, 1997). To cross-validate the self-perceived academic success measure within the CAMP data set, I tested the relations between self-perceived academic success and a single-item measure of academic success, as reported by parents at a single time over the course of the study. Across the longitudinal sample, self-perceived and parent reported academic success correlated significantly between .37 to .43, indicating a moderate relation between the two measures. Cronbach's alpha for the three-item construct of self-perceived academic success ranged from $\alpha = .71$ to .73 across the five waves of data among all boys in the longitudinal sample.

Hopeful Future Expectations. To assess participants' hopeful future expectations, the CAMP study adapted the Hopeful Future measure (Schmid, Phelps, & Lerner, 2011). Hopeful future expectations was a measure of how well a participant believed his or her life would be as an adult, with regard to health, family, and self-concept (Schmid et al., 2011). The scale began with a general prompt: "*Think about your future. What will your life be like when you grow up? "When I grow up…*" The response format ranged from 1 "*Not at all like me"* to 5 "*Exactly like me.*" Higher scores indicated higher expectations of the likelihood that specific future outcomes will occur. Of the seven items included in the CAMP pilot study, four were dropped due to poor reliability, leaving three items. The items were "*I will have a happy family*," "*I will be healthy,*" and "*People will think I am a good person*." Cronbach's alphas for all boys in the longitudinal sample of the CAMP study ranged from .70 to .71.

Procedure

Participant recruitment for the CAMP study involved sampling both Scout and non-Scout groups. For both groups, sample recruitment began through the recommendations of administrators of the Philadelphia-area Cradle of Liberty (COL) Council. These colleagues recommended that the structure of Cub Scout programs be leveraged to recruit a Scout sample, and to use school connections that the Council had, in order to recruit a non-Scout comparison sample. Scout units and schools were contacted and invited to participate.

To obtain parental consent, research partners (pack leaders or school staff) gave each child materials to take home to his/her parent or guardian. These materials were: a letter explaining the study and providing the researchers' contact information; a parent consent form; a parent questionnaire (PQ); and an envelope to confidentially return the PQ to the collection site. Research partners were responsible for collecting returned materials, and for keeping track of which children had obtained parental consent. A small percentage of collection sites asked for assistance from the research team in administering the surveys.

Survey materials were sent to participating collection sites, including instructions for data collection, surveys, various supplies, and a small gift for the participants to thank them for their participation. A detailed protocol and an online webinar were used to facilitate correct administration, collection, and return of all study materials to the research team. Administration of the survey began by obtaining child assent and reading the general instructions on the front page of the questionnaire to the children. Participants were instructed that they could skip any questions that they did not want to answer, or select "*I don't know.*" Participants completed the cover page with their name, signature, date, and birthday, and were informed that all identifying information would be detached from their questionnaires and kept confidential.

Research partners were instructed to allow 15 minutes for completion of the survey, which, for Scouts and non-Scouts, occurred during Cub Scout pack meetings or the school day, respectively. In order to minimize testing bias, research partners were instructed to allow the participants to complete the survey with minimal interference from adults, other Scouts, and other students. Assistance with reading and word comprehension was allowed when necessary. The vast majority of participants were able to complete the questionnaire within the 15 minute time frame.

A Review of the Chase (2014) Findings

As shown in Figure 1, in the exploratory factor analyses (EFAs) conducted by Chase (2014), findings indicated that SOC items did not map onto the differentiated SOC components of S (Selection), O (Optimization), or C (Compensation), but were instead differentiated into factors characterized by “self-help” and “seeking-help” strategies, that is, factors that represented two sets of goal pursuit strategies. The first factor was self-help, or individually-oriented SOC (ISOC), characterized by demonstrating ingenuity, and the ability for youth to draw on individual strengths to solve a problem. In contrast, the second factor was seeking-help, or other-oriented SOC (OSOC), characterized by asking for help, an important strategy for youth that demonstrates the ability to take advantage of available resources, such as parents and teachers, to achieve a goal.

Chase described this two-factor solution as an instantiation of concepts associated with RDS metatheory (Overton, 2013, 2015). RDS metatheory stresses agency, and leads to the idea that an individual’s strengths are a key contributor to building adaptive developmental regulations (Lerner, Lerner, Bowers, & Geldhof, 2015). RDS metatheory also emphasizes autopoesis (or self-construction), and is linked to the notion that an individual must also identify,

access, and use contextual resources available to them in order to thrive, to show PYD (Gestsdóttir & Lerner, 2007; Geldhof, Little, & Colombo, 2010). In the case of Chase (2014), the factors in the two-factor solution represented part of the adaptive developmental regulations needed to thrive (Brandtstädter, 1998; Lerner, 2004).

Although the two-factor model explained above had not been formally identified in previous operationalizations of SOC, it was not completely without precedent. EFAs conducted using SOC data from the 4-H Study of PYD (Lerner et al., 2005) found comparable response patterns, with a similar two-factor model identified as a possible solution (Geldhof et al., 2014). The fact that this factor structure had been identified before, using a separate data set (with items that have since been modified for the current study of younger youth), and was found to be invariant in a longitudinal CFA in the Chase (2014) study, gave further support to the possibility that the two-factor structure of SOC is not a unique artifact of the CAMP study data set but, instead, a plausible factor structure of SOC in elementary school youth.

Having established psychometric validity for the two-factor model of SOC in elementary school-aged boys, Chase (2014) analyzed the relations between the two SOC factors and a theoretically important outcome, self-perceived academic success. Table 1 shows that both OSOC and ISOC were correlated with self-perceived academic success, but ISOC was found to be more highly correlated with self-perceived academic success, and with greater consistency. These correlations could not be interpreted causally, but they did provide guidance for future analyses, and suggested possibilities for considering which aspects of ISR may be associated with successful students, and may, therefore, be targets for interventions aimed at enhancing academic performance. Analyses of the relations between SOC and self-perceived academic

success, as well as additional analyses that were conducted in this dissertation, are described below.

Plan of Analysis

Findings from Chase (2014), suggested a two-factor model of SOC among elementary school aged boys, as well as some possibilities as to how these two factors may relate to self-perceived academic success. Based on these and other findings cited in Chapter 1 (e.g., Geldhof et al., 2014), I generated new research questions that were addressed in this dissertation. These research questions were:

1. Is the two-factor model of ISOC and OSOC, as well as the outcome of self-perceived academic success, invariant across Grades 1 through 5 of the CAMP study?
2. Does self-perceived academic success change over the elementary school years, that is, is there an identifiable trajectory (or multiple trajectories) of self-perceived academic success across grades?
3. Do ISOC and OSOC change over the elementary school years, that is, are there identifiable trajectories of ISOC and OSOC?
4. If growth mixture models can be specified, does group membership in self-perceived academic success trajectories relate to similar trajectory classes of focal predictors such as ISOC and OSOC, and predictors of secondary interest such as hopeful future expectations?
5. Are Cub Scouts more likely to belong to any of these trajectory classes, that is, high or low levels of ISOC, OSOC, or self-perceived academic success?

Results

Before my research questions could be analyzed, several preliminary issues had to be addressed to ensure that the CAMP study data set could be meaningfully assessed longitudinally. The first such step was to determine whether the vocabulary and grammatical structure of the CAMP study questionnaire (including the measures relevant to this dissertation) were simple enough to be understood by all participants, including participants in Grade 1. To address this issue, I analyzed the reading level requirements of the CAMP study questionnaire to determine whether the youngest participants should have been capable of understanding the questionnaire items.

Preliminary Analyses

I used an online resource called “The Hemingway App” to determine the literacy level required to complete the questionnaire (see www.hemingwayapp.com). I found that all scales in the CAMP questionnaire were categorized as "Grade 0 reading level" (i.e., simple enough to be read by current Grade 1 students). This finding confirmed that the grammatical structure and content of the items were simple enough to be understood by Grade 1 participants, and, therefore, by all participants in the current analysis who were at a Grade 1 or higher reading level. Of course, not all students are reading-proficient at their grade level, but research partners who administered the questionnaires were instructed to assist participants if they had problems with reading and vocabulary. Therefore, due to the assistance of research partners, participants should have been able to understand the questionnaire even if they were not able to read every item on their own.

Establishing Participants' Grade in School

Because the CAMP study data set was originally structured by wave, I began by establishing the grade level of each participant in order to restructure the data set by grade for later longitudinal analyses. Participants reported their grade in school most reliably in Waves 1, 3, and 5, when there was no ambiguity about which grade participants were in school (i.e., the beginning of the new school year). In contrast, some participants took the survey in May or June for spring data collection, and they may have reported themselves as having "graduated" to the next grade in school. Therefore, I used responses from fall waves to determine each participant's grade at each wave in the CAMP study.

Establishing a Longitudinal Data Set

Next, I established a data set to be used for the remainder of the analyses. To ensure that intraindividual change could be assessed, I only included participants who were surveyed across multiple waves. However, before I could establish this longitudinal sample, I needed to determine whether the pattern of participation across grade and wave included sufficient representation for all relevant variables for all sub-samples of interest, such as Cub Scouts and non-Cub Scouts, to conduct meaningful longitudinal analyses.

I initially identified 1,497 male participants as longitudinal (i.e., they had participated in two or more waves of the CAMP study). Of these 1,497 male participants, 42 were out of grade-range (i.e., not in Grades 1 through 5) when they joined the CAMP study, and thus were dropped from my analyses. Therefore, 1,455 longitudinal, male participants remained in the analytical sample. Of these 1,455 longitudinal participants included in my analyses, 1,129 were Cub Scouts and 326 were non-Scouts.

Of the 1,455 boys with 2 or more waves of data in the study, 800 (55%) participated at Grade 1, 1,012 (70%) participated at Grade 2, 1,011 (70%) participated at Grade 3, 1,033 (71%) participated at Grade 4, and 858 (59%) participated at Grade 5. However, for reasons that will be explained when I discuss how I addressed Research Question 1, only participants who participated in two or more *grades* between Grades 2 through 5 were considered in the final longitudinal model. This decision left 959 participants in the longitudinal sample to be used in model testing.

Characteristics of the Cross-Sectional and Longitudinal Samples

As reported by parents, the 2,752 participants in the full CAMP study sample were between six and 11 years old at Wave 1 of the CAMP study (M_{age} = 8.48, SD = 1.59). Of the 1,802 (65.5%) participants whose parents reported their racial ethnic background, the majority of them were European American (70.9%), with other racial/ethnic backgrounds being African American (14.6%), Latino/a (6.7%), Asian American (2.7%), multiracial or multiethnic (3.2%), and Native American (0.4%). In addition, 1.6% of participants reported their race/ethnicity as "Other".

Analyses in this dissertation required the use of a longitudinal sample, as specified above. This longitudinal sample included 959 boys (M_{age} = 8.30, SD = 1.12). Of these 959 boys, parents of 689 of them (71.8%) reported their racial/ethnic background. These participants were predominantly European American (76.2%), with other racial/ethnic backgrounds being African American (10.0%), Latino/a (5.2%), Asian American (3.5%), multiracial or multiethnic (2.5%). In addition, 2.6% of participants reported their race/ethnicity as "Other".

There were 1,725 (62.7%) parents who reported average household income in the overall sample. They had an average estimated household income of $64,400. Average income for the

longitudinal sample was somewhat higher – of the 742 (77.4%) of longitudinal participants' parents reporting, they had an average estimated household income of $70,600.

In addition, the neighborhood of each participant in the CAMP study was rated on an urban-rural scale (Hilliard et al., in press), in which "1" represented the most urban, high density neighborhoods, and "12" represented the most rural, low population neighborhoods. Participants in the overall sample lived in slightly more urban areas ($M_{urban} = 5.07$, $SD = 2.32$) compared to the longitudinal sample ($M_{urban} = 5.21$, $SD = 2.29$), though the magnitude of this difference was trivial.

The CAMP study also included a measure of neighborhood racial/ethnic diversity (Hilliard et al., in press). Neighborhoods ranged in diversity from 1 to 100, with 1 representing lowest levels of racial/ethnic diversity, and 100 representing the highest levels of racial/ethnic diversity. Participants in the overall sample lived in slightly more diverse areas ($M_{diverse} = 52.35$, $SD = 23.76$) compared to the longitudinal sample ($M_{diverse} = 50.70$, $SD = 22.36$).

In sum, the longitudinal sample was slightly less diverse (both in regard to individual and neighborhood characteristics), marginally less urban, and slightly higher in SES than the overall sample. However, these differences are common when identifying an across-grade longitudinal sample (e.g., Lerner et al., 2005) and do not represent a major source of bias in the current study. Having established this longitudinal sample, I explored each of my research questions through a series of analyses explained below.

Research Question 1: Invariance Testing

I began my analyses by addressing Research Question 1, "Is the two-factor model of ISOC and OSOC, as well as the outcome of self-perceived academic success, invariant across Grades 1 through 5 of the CAMP study?" To answer this question, I conducted tests of

measurement invariance. Unlike Chase (2014), a study that established invariance of the two-factor model across waves of the CAMP study, I conducted a multiple-group longitudinal test of invariance by grade in school, across Grades 1 through 5.

I decided to build a measurement model across grade, rather than wave, for two reasons. First, many of my developmental questions of interest were relevant to curriculum changes and academic expectations that are grade-specific, instead of wave-specific. Therefore, trajectories across grade will be more sensitive to, and relevant for, these grade-level effects. Second, my preliminary longitudinal analyses of CAMP study data found that there were some issues related to the amount of time between waves that created specific challenges, such as colinearity of auto-regressive loadings of self-perceived academic success. This colinearity may be explained by the fact that very little time (in some cases, fewer than 60 days) had passed for some participants between waves of data collection. Therefore, it is possible that not enough time had passed for changes in self-perceived academic success to be detected, for example, and responses remained unchanged as a result. For these two reasons, I chose an across-grade measurement model for these analyses.

Deciding between Full-Grades and Half-Grades

Before any testing of longitudinal data could be conducted, I had to make a decision regarding how data were to be considered in regard to time. Participants in the CAMP study had the opportunity to take the survey on two occasions while in the same grade, as surveys were administered in the fall and spring of each school year. This design gave me the opportunity to measure change at multiple points within each grade (i.e., Grade 2 = fall, and Grade 2.5 = spring, in the half-grade model). However, the goal of my analyses was to compare change across elementary school grades. Therefore, in order to have a single set of responses for each grade in

school, I had the alternative option of choosing a single set of responses for each grade by defaulting, for example, to the score that was received in the fall of Grade 2 (i.e., the full-grade model). If data from the fall of Grade 2 did not exist for a participant, data from the spring of Grade 2 would be used.

There were potential benefits to either decision. The benefits of the half-grade model were that I would have made use of all available data, instead of discarding a second set of responses within a grade. In addition, the half-grade model would have had eight data points across four grades in school (as many as 5 points for any individual participant), which could support more nuanced trajectory analyses (i.e., both quadratic and cubic models). In addition, the time-lag between grades would have been more consistent, as I could have assumed that participation occurred during a season of a year (e.g., spring of Grade 3) instead of an unknown time across a whole school year (e.g., an unknown time during Grade 3).

However, the full-grade model had several advantages as well. The four occasions of measurement (choosing from one of two waves into each grade) would mean that there would be more participants represented in each grade – an important consideration, given that I would eventually need to test sub-groups of the overall sample – particularly if the most appropriate GMMs identified multiple trajectory classes. Relatedly, Table 2 illustrates that across-grade representation was more complete with a combined, full-grade model, due to the larger percentage of participants who participated in any given full grade. Each full grade was, therefore, more likely to have sufficient representation for across-grade invariance testing than would have been possible in the half-grade model. Finally, interpretation would be simpler for a full-grade model, as I was particularly interested in how SOC and self-perceived academic success changed from grade to grade, and a full-grade transition provided a more relevant

interpretation. In effect, I had to choose between “stretching” the data across eight occasions of measurement in the half-grade model, or “squeezing” the data into four occasions in the full-grade model.

I attempted to run both models (half-grade and full-grade) in Mplus for invariance testing (the results of which are explained below) to determine if one or both of these models could be used in subsequent analyses. The sample consisted of 959 participants who took part in the survey in at least two elementary school grades (among Grades 2-5). However, as the study only spanned 2.5 years, no individual participant could have participated across all four grades. As I noted above, the across-grade representation in the half-grade model was necessarily less than that of the full grade model. As a result, an insufficient number of participants took part in the surveys across each occasion of measurement (ranging from 9% to 36%), leading to a failure of model convergence. Therefore, invariance testing could not be conducted with the half-grade model. Next, I attempted to run the invariance model across full grades. The across-grade representation for the full-grade model ranged from 15% to 45%. Although the representation was still mediocre, there was sufficient representation across grades for the invariance models to converge. Therefore, due in part to the practical requirements of model testing, the full-grade model was used for all subsequent analyses.

Measurement Invariance by Wave in Each Grade

As shown in Figure 2, my analyses for Research Question 1included tests of configural, loading, and intercept invariance across Grades 1 through 5. Measurement invariance testing was necessary to determine whether the loadings and intercepts of each indicator were equivalent across grades. By establishing this measurement invariance, I could assume that, because the constructs were defined in the same operational manner for each group, the construct’s variance,

correlations, and mean differences could be compared meaningfully and with quantitative accuracy (Cheung & Rensvold, 2002; Little, 2013).

Before I could test measurement invariance across grade in school, however, I had to account for possible differences in responses based on the wave in which a participant was in a particular grade in school. This test accounted for differences among participants who began participating in the CAMP study at later waves, or aged into a grade later in the study (i.e., cohort differences within each grade). Therefore, I began my analyses with a series of invariance tests to determine whether participants who were in Grade 1 at their first wave of testing, for example, had different response patterns when compared with participants who were in Grade 1 at Wave 3.

I began with participants in Grade 1, and tested their responses for measurement invariance across wave of participation. I included all three factors in the invariance testing, allowing ISOC and OSOC to covary within wave due to their theoretical relations. Although there are many ways to delineate reasonable model fit, many researchers use some or all of the following cutoffs: Root Mean Square Error of Approximation (RMSEA) < .08, Comparative Fit Index (CFI) > .90, and Tucker Lewis Index (TLI) > .90 (Little, 2013).

I began with configural invariance testing, which is used to determine whether the patterns of factor loadings across waves are similar (Little, 2013). The ‘full model’ version (i.e., the model that included ISOC, OSOC, and self-perceived academic success) demonstrated model fit in the configural invariance model. I next tested the model for loading (weak) invariance. This test was conducted to determine whether items loaded onto their factors similarly across waves of measurement, and was necessary to ensure that meaningful comparisons could be made across multiple waves of testing (Brown, 2006). However, Table 3 shows that the full model did

not meet the requirements for loading invariance, with a change in CFI greater than .01 (Cheung & Rensvold, 2002).

To determine the source of this non-invariance, I tested the two-factor model of SOC for invariance across wave, separately from the self-perceived academic success construct, in order to isolate possible differences in the structure of SOC factors. Table 3 shows that the results were the same in the two-factor model of SOC as in the full model; despite demonstrating adequate model fit in the configural invariance model, the loading invariance model did not meet the requirements for loading invariance, with a change in CFI greater than .01.

Having failed to demonstrate invariance among Grade 1 participants across waves (notably, a detail that had *not* been demonstrated by Chase, 2014, who had tested invariance across wave without taking into account grade in school), I decided that further testing should be conducted to determine whether Grade 1 participants had a different response pattern than other grade levels with regard to ISOC and OSOC. Therefore, I tested whether a single global factor of SOC demonstrated model fit and invariance among Grade 1 participants. Modification indices suggested a single modification in the one-factor model by allowing residual covariance of the two items that made up OSOC in the two-factor SOC model. With this modification included, Table 3 shows that the one-factor (i.e., global) SOC model did indeed demonstrate loading invariance. The one-factor model also demonstrated intercept invariance, a final step that involved testing the latent mean structure across waves of measurement (Little, 2013).

Having observed an invariant, albeit modified, solution for the SOC model for Grade 1 participants, I continued to test each subsequent grade individually for invariance across waves. For Grade 2 participants, I began by testing the original “full model” which included the two-factor measure of SOC, and self-perceived academic success. For Grade 2 participants, and

indeed for all participants in Grades 2 through 5, the full model showed sufficient model fit, and demonstrated configural, loading, and intercept invariance without any modifications required (see Tables 4 through 7). Therefore, no significant differences in response pattern were identified in OSOC, ISOC, or self-perceived academic success in Grades 2, 3, 4, and 5, respectively, based on the wave in which those data were collected.

The above findings demonstrated that there was indeed invariance across wave within each elementary school grade, although the structure of SOC had only one factor among Grade 1 participants (instead of the two-factor model, as identified in all other elementary school grades). This finding of invariance allowed me to conduct subsequent analyses under the assumption that OSOC, ISOC, and self-perceived academic success factors were equivalent among same-grade participants irrespective of the wave (i.e., cohort) within the CAMP study data set. However, as both a practical and a theoretical matter, Grade 1 participants were not included in further analyses, as the SOC construct manifested itself differently among these Grade 1 youth, making comparisons between Grade 1 and all other grades untenable.

Invariance across Grade in School

Having established invariance within grades across wave, I next tested whether the two-factor model of SOC and self-perceived academic success was invariant across grades in school by measuring whether the longitudinal model demonstrated configural, loading, and intercept invariance in the four remaining grades (i.e., Grade 2 through Grade 5). Such measurement invariance would confirm that SOC and self-perceived academic success demonstrated measurement equivalence across grade in school and, by inference, across developmental levels. Therefore, I tested the invariance of the full model across grade in order to be confident that

results from subsequent longitudinal models regarding developmental patterns were both interpretable and trustworthy.

Typically, invariance testing would include all relevant groups (at this point in the analyses, now Grades, 2, 3, 4, and 5) in one model. However, the CAMP study occurred over the course of only 2.5 years. Therefore, assuming no participants skipped a grade in school, a participant could only have spanned as many as three years of elementary school, such as Grades 2, 3, and 4, during the course of the CAMP study. Therefore, due to this design-based missingness, no single participant could have participated in all four grades. The statistical software program I used for these analyses, Mplus version 7.3, requires at least a small percentage of representation, or "covariance coverage" for each variable tested, in order to conduct invariance testing. To solve this problem, I conducted two separate invariance models. The first model tested for invariance across Grades 2 through 4. The second model tested for invariance across Grades 4 and 5. In this way, if both of these tests found invariance, I would be able to interpret these findings as invariant across all four grades. The design-based missingness remaining in the model could be interpreted as "Missing Completely at Random" (MCAR), and therefore was not considered a source of bias in this study.

Table 8 shows that the full model across Grades 2 through 4 demonstrated good model fit. This model also showed configural, loading, and intercept invariance across all grades tested. Next, I tested the full model across Grades 4 and 5. This model also demonstrated sufficient model fit, as well as configural, loading, and intercept invariance across Grades 4 and 5 (see Table 9). Neither of the above models were modified in any way as a result of modification indices. Due to the results of the above invariance testing models across Grades 2 through 5, I

was able to assume measurement equivalence of the full model (i.e., OSOC, ISOC, and self-perceived academic success across grades) in all subsequent analyses.

Research Question 2: The Self-Perceived Academic Success Growth Mixture Modeling

In this section, I addressed Research Question 2, "Does self-perceived academic success change over the elementary school years, that is, is there an identifiable trajectory (or multiple trajectories) of self-perceived academic success across grades?" To address this question, I conducted a series of Growth Mixture Models (GMM; Muthén & Muthén, 2000) of self-perceived academic success to determine whether distinct trajectory classes of self-perceived academic success could be identified in the longitudinal CAMP study sample. A GMM is similar to latent growth curve modeling, in that it can be used to assess interindividual differences in intraindividual change by estimating intercept and slope parameters across occasions of measurement, resulting in growth trajectories (Muthén et al., 2002). However, unlike the assumption of a single trajectory in a latent curve analysis, GMM allows for distinct groups of participants to be identified based on their intercept and slope values, resulting in multiple growth trajectories.

Although GMM can often result in a more nuanced description of growth patterns than a single latent curve, GMM has a disadvantage of being computationally intensive; especially when there are no restrictions on the assumptions of variance in the model (Collins & Lanza, 2010). Therefore, as needed, I estimated models that included some restrictions, such as only allowing intercepts to vary across trajectory classes, instead of allowing the estimation of variances in both intercept and slope within each trajectory class. The models were further simplified by using composite scores for self-perceived academic success at each grade, allowing the models to be computed more easily. Whereas the use of composite scores did take away

some of the nuances of the latent factors, the use of composite scores was justifiable because the factor loadings of the individual items for each factor were sufficiently similar such that averaging the scores was unlikely to bias the data. Last, within all of the GMMs that included a quadratic slope, I fixed the variance of the quadratic slope to zero, as the variance of a quadratic slope is particularly computationally intensive, and unlikely to reflect actual data. Such restrictions helped to develop a realistic growth model that could still be estimated by the Mplus version 7.3 software.

I began testing GMMs with varying numbers of trajectory classes (from one to seven classes) to determine which model would be used in subsequent analyses. A one-class, quadratic solution, for example, would indicate that the longitudinal sample would be best represented by a single curvilinear trajectory. A three-class quadratic solution, on the other hand, would represent the data as three sub-samples of the overall longitudinal sample, each with different intercepts, linear slopes, and quadratic slopes.

While initially running these GMM analyses, I accounted for the fact that all quantitative data collected in the CAMP study had a nested data structure, as sampling occurred through the schools or Cub Scout packs of participants. To take this nestedness into account in my analyses, I used the TYPE=COMPLEX option in Mplus version 7.3, using “School” for comparison school boys, and “Pack” for Cub Scout participants, as the clustering variable. By including the pack or school of the participant, I was able to properly adjust the standard errors, thereby avoiding the potential biases of ignoring nestedness in the CAMP study sample.

I ran the GMM analyses with and without accounting for nested data, and found no differences in any fit indices. Therefore, I decided to maintain the assumption of independence, and no longer use the TYPE=COMPLEX option (i.e., I opted to consider each participant

individually, instead of grouped together meaningfully by his school or Cub Scout pack) in subsequent analyses. Removing the TYPE=COMPLEX option allowed me to include the Bootstrapped Likelihood Ratio Test (BLRT), which is critical for evaluating the number of trajectory classes and is, unfortunately, not available in conjunction with the TYPE=COMPLEX option in the Mplus software program.

Trajectory Class Enumeration for Self-Perceived Academic Success GMMs

I made the decision regarding the number of trajectory classes based on comparing fit indices and theoretical interpretability of a variety of GMM solutions. An ideal model would have the lowest Bayesian Information Criterion (BIC: Raftery, 1995) and Akaike Information Criterion (AIC: Akaike, 1974) values, along with the highest entropy values (*E*), which indicates the degree to which participants can be accurately classified into trajectory groups (Collins & Lanza, 2010). The Lo-Mendell-Rubin Likelihood Ratio Test (LMR: Lo, Mendell, & Rubin, 2001) and Bootstrap Likelihood Ratio Test (BLRT) should also show a significant *p*-value, indicating that the inclusion of an additional group leads to improved model fit (Nylund, Asparouhov, & Muthén, 2007). Using the above criteria, I chose the most parsimonious and theoretically meaningful GMM solution. Below, I describe the findings of my GMM analyses, which provided me with the model of self-perceived academic success across the elementary school years used in all subsequent analyses in this dissertation.

One of the strengths of the GMM analysis technique is that it provides an average intercept and slope for each class, but allows for variation around these estimates, such that members of a trajectory class can be similar, but are not assumed to be exactly the same (Collins & Lanza, 2010). To determine the appropriate number of trajectories, I took into account fit indices, theoretical expectations, and interpretability (Geiser, 2013; Nagin & Odger, 2012). Each

of the fit indices must be as low as possible, with the exception of entropy, which should be as high as possible, with a range of 0.00 to 1.00. However, the class solution should also be chosen based on theory, interpretability, and the substantive questions that are being addressed (Nagin & Odger, 2012). I increased the number of random starts when appropriate to ensure that the models converged and that the solution was stable (Hipp & Bauer, 2006).

I began by freely estimating each parameter, such that the intercepts and slopes were free to vary within each trajectory class. However, in each analysis I conducted, Mplus gave warnings, indicating that the latent variable covariance matrix (i.e., the relation between the slope and intercept) could not be reliably estimated due to the estimation of slope and intercept variance. This type of warning indicated that a freely-estimated variable does not actually have any variance. Therefore, I fixed the variance of the linear slopes and intercepts to be zero within class trajectories each time that Mplus gave a warning, and these changes eventually led to convergence of each GMM. These changes are common in GMM analyses of scale scores (e.g., Callina, Johnson, Buckingham, & Lerner, 2014).

In order to evaluate changes in the AIC, BIC, and entropy, I evaluated each fit index for the models with one to seven classes. I began by conducting linear GMMs (i.e., models that only included an intercept and linear slope for each trajectory class) ranging from a one-class solution to a seven-class solution. Next, I ran the same seven models with the addition of a quadratic slope. Each of the models with quadratic slopes resulted in an improved (lower) Loglikelihood value when compared with the linear models, had fewer errors in the model estimation due to non-positive definite solutions, and generally improved the fit indices. Therefore, only the models with quadratic slopes were considered below.

Then, I compared the seven GMMs with quadratic functions to determine which had the best model fit, though still remaining theoretically meaningful and interpretable. Notably, BIC and AIC were reduced (i.e., they improved) with every additional class added, until they reached their lowest point at the five-class solution. Table 10 shows that entropy, however, improved steadily until it peaked at the six-class solution. The five- and six-class models each included a relatively small trajectory class group (i.e., 13 and 14 participants, respectively, or 1.4% of the overall sample). Although it would have been defensible to simply remove these outliers from model testing, the fact that this group persisted across multiple GMM solutions indicated that it may have represented a small but informative sub-sample of participants. As such, I decided to keep the participants from the small trajectory class in the GMM. Therefore I chose the five-, six-, and seven-class solutions for further testing, to determine which of these models was most appropriate. I began by running the LMR and BLRT tests for each model. However, I gave more weight to the results of the BLRT, which simulations have shown to yield more accurate class estimates (Nylund, Asparouhov, & Muthén, 2007).

Results of the LMR and BLRT indicated that the 5-class model was a better fit compared to the four-class model, but that the six-class model was a significant improvement over the five-class model (based on the BLRT). The seven-class model failed to converge when running the BLRT test, which disqualified it as a possibility. Therefore, I chose the six-class model due to strong fit indices and theoretical interpretability.

Notably, the best fitting, six-class solution for self-perceived academic success did not allow for any variation in intercept and linear slope within each group (i.e., the slope variance and intercept variance were set to zero for each trajectory class). Therefore, my analyses, in

effect, were more accurately termed latent class growth analyses (LCGA), as LCGA analysis assumes that there is no variation in slope or intercept within classes.

As shown in Figure 3, the six-class model of self-perceived academic success had three trajectory classes that I termed "Stable" (i.e., there was very little change in scores across Grades 2 through 5) and three trajectory classes that I termed "Changers" (i.e., there was a substantial change in intercept from Grades 2 through 5). I named the three stable trajectory classes "*High, Stable,*" "*High/Moderate, Stable,*" and "*Low/Moderate, Stable.*" I named the three changer classes "*High, Decreasing,*" "*Moderate, Decreasing,*" and "*Low, Increasing*."

Some of the six above-mentioned trajectory classes demonstrated multifinality (the concept that individuals may start from the similar points, but have different developmental outcomes – e.g., Kruglanski et al., 2013). For example, The "*High, Stable*" trajectory class started at the same point as the "*High, Decreasing*" trajectory class, but reached a very different level by Grade 5. In addition, other class trajectories demonstrated equifinality (the concept that individual may begin at different points, but arrive at the same developmental outcomes– e.g., Kruglanski et al., 2013). For example, the "*Low, Increasing*" trajectory class represented dramatic change across the elementary school years, arriving at the same outcome as participants in the "*High, Stable*" trajectory class by Grade 5. In the analyses that followed, I used participants' membership in each of these trajectory classes as the outcome of interest for predictors such as OSOC and ISOC.

Research Question 3: ISOC and OSOC Growth Mixture Modeling

In this section, I addressed Research Question 3, "Do ISOC and OSOC change over the elementary school years, that is, are there identifiable trajectories of ISOC and OSOC?" To address this question, I conducted a series of Growth Mixture Models (GMM; Muthén &

Muthén, 2000) of ISOC, followed by similar tests of OSOC, to determine whether distinct trajectory classes of each of these SOC variables could be identified in the longitudinal CAMP study sample.

ISOC GMM Trajectory Class Determination

As with the self-perceived academic success GMM analyses, I decided the number of ISOC trajectory classes based on comparing fit indices and theoretical interpretability of a variety of GMM solutions. Once again, I began by conducting linear slope GMMs ranging from a one-class ISOC solution to a seven-class ISOC solution. Next, I ran the same seven models with the addition of a quadratic slope. With the exception of the two-class quadratic slope GMM, each of the models with quadratic slopes resulted in an improved (lower) Loglikelihood value when compared with the linear models, had fewer errors in the model estimation due to non-positive definite solutions, and generally improved the fit indices (BIC, AIC: see Table 11). Next, therefore, I compared the seven ISOC GMMs with quadratic functions to determine which model best fit the data.

To determine the appropriate number of ISOC trajectory classes, I once again took into account fit indices, theoretical expectations, and interpretability (Geiser, 2013; Nagin & Odger, 2012). I evaluated the changes in the AIC, BIC, and entropy by evaluating each fit index for the seven trajectory class solutions. Notably, BIC was at its lowest point at the three-class solution. In contrast, AIC showed the lowest value, and entropy peaked, at the seven-class solution (see Table 11 for fit indices). Therefore, I chose the three- through seven-class solutions for further testing, to determine which of these models was most appropriate. When conducting the LMR and BLRT tests for each model, I found that the three-class and four-class solutions were the

only solutions for which the BLRT test would converge, meaning that testing the five-, six-, and seven-class solutions were removed from consideration.

Both the three-class and four-class solutions had a non-significant LMR values (p = .12 and .11, respectively) and a significant BLRT value (p < .001 and .001, respectively). Therefore, I had to decide on the three or four-class solution based on the BIC value, due to these contradictory recommendations, and other considerations such as parsimony and interpretability of the model. The BIC was slightly lower (i.e., better) for the three-class solution. In addition, the four-class solution had a trajectory class with only six members (i.e., 0.6% of the total sample), making that particular trajectory class potentially difficult to interpret, and less useful for subsequent analyses. Therefore, I chose the three-class GMM solution for ISOC to be used in subsequent analyses, as shown in Figure 4.

OSOC GMM Trajectory Class Determination

Next, I conducted the same series of tests explained above for ISOC (the number of class trajectories, cross-tabulation with self-perceived academic success trajectory classes, and BCH tests of means) but for OSOC. Therefore, I conducted my final set of GMM analyses to determine the most appropriate number of OSOC trajectory classes to include in the final model, based on comparing fit indices and theoretical interpretability of each GMM solution. Once again, I began by conducting linear, than quadratic slope GMMs, ranging from a one-class, to a seven-class OSOC solution. Table 12 shows that the models with quadratic slopes resulted in improved (lower) Loglikelihood values when compared with the linear models, resulted in fewer model estimation errors, and generally improved the fit indices (i.e., BIC, AIC). Therefore, I used only the seven quadratic OSOC GMMs to determine which had the best model fit.

To determine the appropriate number of OSOC trajectory classes, I once again evaluated the changes in the AIC, BIC, and entropy by evaluating each fit index for the seven trajectory class solutions. AIC values were at their lowest point for the five-class solution, and BIC was at its lowest point at the five-class solution. However, entropy rose steadily until peaking at the six-class solution (see Table 12 for fit indices). I attempted to conduct a seven-class solution as well, but the model failed to converge. Therefore, I chose the five- and six-class solutions for further testing, to determine which of these models was most appropriate. When conducting the LMR and BLRT tests for each model, I found that the five- and six-class models each had a significant p-value ($p < .001$) for the BLRT test. However, the six-class solution had a non-significant LMR ($p = .14$), whereas the five-class solution had a significant LMR ($p <.05$). This difference made a strong case for the five-class solution, which also happened to be relatively easy to interpret. Therefore, I chose the five trajectory class GMM solution for OSOC to be used in subsequent analyses, as shown in Figure 5.

Research Question 4: ISOC, OSOC, and Self-Perceived Academic Success

I next addressed Research Question 4, "If growth mixture models can be specified, does group membership in self-perceived academic success trajectories relate to similar trajectory classes of focal predictors such as ISOC and OSOC, and predictors of secondary interest such as hopeful future expectations?" My first step was to cross-tabulate the most likely class membership for academic success with most likely trajectory class membership for both SOC variables. This cross-tabulation procedure was straight-forward, but dependent on high levels of entropy, as discussed below. Cross-tabulating self-perceived academic success in conjunction with ISOC and OSOC trajectory classes was a useful way to determine whether ISR attributes were related to self-perceived academic success trajectory class membership.

In addition to the cross-tabulation, I used the six-class self-perceived academic success GMM solution to determine whether mean levels of OSOC and ISOC differed across trajectory groups by pairwise comparisons of means, using the three-step procedure explained by Asparouhov and Muthén (2014). This analysis was used to determine whether there were different levels of ISOC and OSOC across self-perceived academic success trajectory classes. A benefit of including this analysis in addition to the cross-tabulation analyses described above was that mean levels of ISOC and OSOC for each participant were free of the potential bias implied by the lack of entropy in the ISOC and OSOC GMM solutions. Mean levels of ISOC and OSOC at each grade have the limitation of being insensitive to intraindividual change. However, in combination with the cross-tabulation analysis, I used pairwise comparisons of means to triangulate my findings.

The above analyses helped me to determine how, and at what developmental level, various ISR attributes related to a hypothesized shift in priorities in regard to academic skills. That is, if self-directed, ISOC attributes related to success in late elementary school, for example, educators would benefit from promoting ISOC attributes as a high priority in their classrooms. The following sections describe the results of these analyses.

ISOC and Self-Perceived Academic Success Trajectory Class Cross-Tabulation

Having identified a six-class solution for self-perceived academic success and a three-class solution for ISOC, I next analyzed whether membership in ISOC trajectory classes was related to membership in self-perceived academic success trajectory classes. To carry out this analysis, I first had to establish that the distribution of ISOC trajectory classes and self-perceived academic success trajectory classes were related *overall*. This assessment could be determined by observing patterns of class membership to determine whether they were significantly different

than they would have been if there were no relations between ISOC and self-perceived academic success trajectory classes. The null hypothesis would be, then, that class membership should have been equally distributed. Therefore, I conducted a Pearson Chi-square analysis. Traditional Chi-square analyses require that at least 80% of the cells have expected frequencies of five or more cases (Miller & Siegmund, 1982). In the current analysis, all but one of the cells (96%) had five or more expected participants. Therefore, I was able to use the standard Pearson Chi-square test. This analysis found that ISOC and self-perceived academic success classes were related, with χ^2 (10, 959) = 138.38, $p < .001$.

Having shown that a relationship did exist between the ISOC and self-perceived academic success trajectory classes overall, I then determined which of these cells had more representation than expected, and which cells had less than expected. If my hypothesized relation between ISOC and self-perceived academic success trajectory classes was correct, then trajectory classes with similar intercepts and slopes would have shown greater than expected percentages of overlapping members. Following this same logic, I hypothesized that trajectory classes with different slopes and intercepts should have less overlap.

I found that nearly every ISOC and self-perceived academic success trajectory class with similar shapes did indeed share a greater-than-expected overlap in membership. For example, both ISOC and self-perceived academic success had a "*High, Stable*" trajectory class. Overlapping trajectory class membership was 92.3% higher than expected (130 observed participants, compared with 67.6 expected participants). In contrast, the "*High, Stable*" self-perceived academic success class was 27.3% less likely to overlap with the "*Low/Moderate, Stable*" ISOC class (134 observed participants, compared with 170.6 expected participants).

This pattern of findings supported the hypothesis that similar trajectory classes in ISOC and self-perceived academic success were related (see Table 13 for all expected and observed values).

However, the validity of such cross-tabulation is predicated, in part, on high levels of entropy in both of the trajectory class models, because entropy represents an approximation of the accuracy of trajectory class membership (Collins & Lanza, 2010). The self-perceived academic success trajectory class model had a moderate level of entropy (E = .77). However, the ISOC trajectory class model had a mediocre level of entropy (E = .60).

Another measure of trajectory class membership accuracy considers the average latent class probabilities for most likely latent class membership. This measure was stronger for the ISOC classes, with an average probability of 0.805. This higher probability of trajectory class membership strengthens the argument that the cross-tabulation of ISOC and self-perceived academic success trajectory classes can be meaningfully interpreted. Nevertheless, likely trajectory class membership should not be taken at face-value, as trajectory class membership was not 100% definitive. Therefore, I conducted additional analyses to provide further evidence for the above finding that ISOC trajectory classes and self-perceived academic success trajectory classes were highly related. These additional analyses are described below.

Three-Step Tests of the Equality of ISOC Means by Self-Perceived Academic Success Trajectory Classes

To further investigate the relations between ISOC and self-perceived academic success trajectory classes, I used the three-step test of equality of means. This test preserved the latent quality of the trajectory class membership (i.e., classification uncertainty), therefore mitigating the issues of entropy in my previous analyses. This test is also known as the Bolck, Croon, and

Hanegaars (BCH; 2004) method, and is often used to examine the relations between predictors (in this case, ISOC) and latent trajectory class membership.

Table 14 shows that the overall BCH test results found that there were significant differences in Grade 2 ISOC mean levels between self-perceived academic success trajectory classes, with χ^2 (5, N = 959) = 60.34, p < .001. Therefore, ISOC means at Grade 2 were significantly different among the self-perceived academic success classes. Notably, the greatest difference in ISOC means was between the "*High, Stable*" self-perceived academic success class, and the "*Low/Moderate, Stable*" self-perceived academic success class, with χ^2 (5, N = 438) = 40.30, p < .001. Mean levels of Grade 2 ISOC were 3.27 in the "*High, Stable*" self-perceived academic success trajectory class, whereas mean levels of Grade 2 ISOC in the "*Low/Moderate, Stable*" self-perceived academic success trajectory class were over a full point higher, at 4.31 (see Table 14 for full details).

When comparing changers (i.e., classes in which participants changed from high to low, or low to high self-perceived academic success across elementary school), Grade 2 ISOC means were not different based on self-perceived academic success. In other words, the ISOC means were consistent with Grade 2 self-perceived academic success scores. For example, the lowest ISOC mean at Grade 2 was among participants in the "*Low, Increasing to High*" self-perceived academic success class, with a mean level of ISOC of 3.05. Therefore, Grade 2 ISOC means (i.e., initial values) were a reliable predictor of current self-perceived academic success, but had no bearing on later levels of self-perceived academic success, such as those at Grade 5.

To determine how ISOC related to self-perceived academic success at later waves, I conducted another BCH equality test of means, using the three step procedure to determine whether ISOC means varied across self-perceived academic success trajectory class at Grade 5.

As shown in Table 17, this analysis found that ISOC means among Grade 5 participants differed according to self-perceived academic success classes, with χ^2 (5, N = 959) = 159.90, p < .001. For example, I compared the "*High, Stable*" self-perceived academic success class with the "*Low/Moderate, Stable*" self-perceived academic success class among Grade 5 participants. There were, once again, significant differences between classes, with χ^2 (5, N = 438) = 67.04, p < .001.

When comparing "Changer" class trajectories among Grade 5 participants (i.e., "*High Decreasing to Moderate*," compared to "*High, Stable*" classes), Grade 5 ISOC also differed, with χ^2 (5, N = 344) = 67.04, p < .001. I conducted similar BCH tests for mean levels of ISOC at Grades 3 and 4, and found similar ISOC mean level differences between classes, all of which supported the same conclusion – that lower mean levels of ISOC were found in lower self-perceived academic success trajectory classes, and higher mean levels of ISOC were found in higher self-perceived academic success trajectory classes. In sum, ISOC mean levels related positively to membership in self-perceived academic success trajectory classes with higher means at the time of measurement. Therefore, mean levels of ISOC and self-perceived academic success trajectory classes consistently related across the elementary school years.

Among "changer" classes, across Grades, ISOC means changed concurrently with the changes in self-perceived academic success. For example, participants in the "*Low, Increasing to High*" self-perceived academic success trajectory class had similar, positive change in ISOC at each Grade.

Although ISOC predicted self-perceived academic success trajectory class membership in all grades, there were notable differences in the degree of the relation as participants advanced in elementary school. Tables 14 through 17 show that across Grades 2 through 5, the overall Chi-

square test values were χ^2=60.34, 57.82, 166.50, and 159.90, respectively. Further, partial eta effect size values across Grades 2 through 5 were (.17, .10, .14, and .22, respectively), suggesting a moderate to high practical significance. In addition, there were 15 Chi-square tests comparing classes by ISOC mean levels in each grade. Of these 15 tests per grade across Grades 2 through 5, there were three, five, 11, and nine significant Chi-square findings, respectively (see Tables 14 through 17 for full details). In sum, mean levels of ISOC were in "lock-step" with self-perceived academic success trajectory classes, whether these classes were changers or stable trajectory classes. This finding supports the results of the cross-tabulation reported above; ISOC is strongly related to self-perceived academic success, and these constructs went from a moderate to high relation, beginning in Grade 2 and peaking at Grade 5.

OSOC and Self-Perceived Academic Success Trajectory Class Cross-Tabulation

I next carried out a similar cross-tabulation analysis as I used for ISOC, to determine whether membership in specific OSOC trajectory classes predicted membership in self-perceived academic success trajectory classes across Grades 2 through 5. To carry out this analysis, I had to determine whether membership in similar OSOC trajectory classes and self-perceived academic success trajectory classes were over-represented to a greater extent than one would expect if OSOC and self-perceived academic success trajectory classes were not related. Therefore, I conducted a Pearson Chi-square analysis. In the current analysis, however, seven of the 30 cells (23.3%) had five or fewer expected cases. Therefore, I used the likelihood ratio Chi-square test, which is more robust with regard to low cell representation (Miller & Siegmund, 1982). This likelihood ratio Chi-square test showed that OSOC and self-perceived academic success classes were related, with χ^2 (20, N = 959) = 64.48, p < .001.

Having shown that OSOC and self-perceived academic success trajectory classes were related, I once again determined which of these cells had more or less representation than expected. As with ISOC, I expected OSOC and self-perceived academic success trajectory classes with similar intercepts and slopes to have greater than expected representation in their corresponding cells.

As with ISOC, the pattern of over-representation and under-representation showed a positive relation between OSOC and self-perceived academic success trajectory classes (i.e., similar trajectories shared a greater-than-expected overlap in membership). Once again, I compared the "*High, Stable*" trajectory classes from each construct as an initial test, with the expectation that there would be substantial over-representation. Indeed, "*High, Stable*" trajectory classes shared 36.6% more participants than expected (164 observed participants, compared with 120.1 expected participants). In contrast, the "*High, Stable*" self-perceived academic success class was 42.5% less likely to overlap with the "*Low/Moderate, Stable*" OSOC trajectory class, (23 observed participants, compared with 40.2 expected participants). Both of these findings supported the hypothesis that trajectory classes in OSOC and self-perceived academic success were related (see Table 18 for full details).

Although the OSOC GMM had a slightly higher level of entropy than the ISOC GMM (E = .69) the level of entropy was still low enough that I conducted additional analyses to provide further evidence to test the above finding that OSOC trajectory classes and self-perceived academic success trajectory classes were highly related. These additional tests are described below.

Three-Step Tests of the Equality of OSOC Means by Self-Perceived Academic Success Trajectory Classes

I conducted another analysis using the equality test of means to determine whether mean levels of OSOC varied across self-perceived academic success trajectory classes. This analysis found that OSOC means among Grade 2 participants and self-perceived academic success classes were not related, with χ^2 (5, N = 959) = 4.74, p = .45 (see Table 19 for full details). Therefore, self-perceived academic success trajectory classes were not significantly related to OSOC means at Grade 2.

To determine whether OSOC related to self-perceived academic success at later waves, I conducted another equality test of means, using the three step procedure to determine whether OSOC means varied across self-perceived academic success trajectory class at Grades 3, 4, and 5. In contrast with the same analysis at Grade 2, OSOC means among Grades 3, 4, and 5 participants did predict self-perceived academic success classes. For example, Grade 5 Chi-Square tests were significant, with χ^2 (5, N = 959) = 19.30, p < .01. Therefore, OSOC means at Grade 5 differed significantly among the self-perceived academic success classes (see Table 22).

As I had done with ISOC means, I compared the OSOC means associated with the "*High, Stable*" self-perceived academic success class with the OSOC means associated with the "*Low/Moderate, Stable*" self-perceived academic success class among Grade 5 participants. There were significant differences between these two classes, with χ^2 (5, N = 438) = 8.41, p < .01. When comparing the "Changer" class trajectory among Grade 5 participants (i.e., "*Moderate, Decreasing to Low*," compared to "*High, Stable*" classes), Grade 5 OSOC predicted self-perceived academic success trajectory class, with χ^2 (5, N = 302) = 14.88, p < .001. However, when comparing the other "Changer" class trajectory among Grade 5 participants (i.e.,

"*High, Decreasing to Moderate*," compared to "*High, Stable*" classes), Grade 5 OSOC did not relate to self-perceived academic success trajectory class, with χ^2 (5, N = 344) = 1.07, p = .30. These findings were consistent across all grades from Grade 3 through Grade 5 (see Tables 20 through 22 for full details).

Unlike ISOC, which had notable differences in the degree of the relation to self-perceived academic success trajectory class membership as participants advanced in elementary school, OSOC predicted self-perceived academic success trajectory class membership in Grades 3 through 5 consistently across grades. Although the relations were consistent, they were also much weaker than ISOC. Tables 20 through 22 show that across Grades 3 through 5, the overall Chi-square test values were χ^2=20.83, 16.59, and 19.29, respectively. Further, partial eta effect size values across Grades 3 through 5 were (.02, .04, and .03, respectively), suggesting a small to moderate practical significance. In addition, of the 15 Chi-square tests comparing classes by OSOC mean levels in Grades 3 through 5, there were two, one, and two significant Chi-square values, respectively. Therefore, OSOC was a relatively weak, but consistent predictor of self-perceived academic success trajectory class membership in Grades 3 through 5.

In sum, OSOC mean levels did not relate to membership in self-perceived academic success trajectory classes among Grade 2 participants, but did relate to self-perceived academic success trajectory class membership among Grade 3 through 5 participants, such that, beginning at Grade 3, higher mean levels of OSOC were associated with membership in self-perceived academic success trajectory classes with higher means at later elementary school grades.

Hopeful Future Expectations Findings

In addition to testing the predictors of primary interest in Research Question 3 (i.e., ISOC and OSOC), the last task was to into account a factor of secondary focus that I believed would

moderate the relations between ISR and self-perceived academic success: hopeful future expectations. Hopeful future expectations was a measure of how well a participant believed his or her life would be as an adult, with regard to health, family, and self-concept (Schmid et al., 2011).

In order to gauge the relevance of my hypothesis that hopeful future expectation moderated the relations between both SOC factors (ISOC and OSOC) and academic success, I conducted preliminary analyses of hopeful future expectations by including the construct in a multiple regression with predictors of ISOC, hopeful future expectations, and a variable that represented an interaction of ISOC and hopeful future expectations, on the outcome variable of interest, self-perceived academic success. I ran these multiple regression analyses for each grade (Grades 2 through 5) and found that, although ISOC and hopeful future expectations each uniquely and significantly predicted self-perceived academic success in all grades, the interaction term was consistently non-significant. I conducted the same analyses for OSOC, hopeful future expectations, and an interaction variable of OSOC and hopeful future expectations on the outcome of self-perceived academic success. Again, no evidence for moderation was found across Grades 2 through 5. This lack of interaction may have been due, in part, to a ceiling effect of hopeful future expectations, as the vast majority of participants reported extremely high scores on hopeful future expectations in the longitudinal sample. Therefore I chose not to pursue further analysis with hopeful future expectations.

Research Question 5: Scouting and Self-Perceived Academic Success

Last, I addressed Research Question 5, “Are Cub Scouts more likely to belong to any of these trajectory classes? (i.e., levels of ISOC, OSOC, and self-perceived academic success).” The majority of participants in the CAMP data set were Cub Scouts, so I sought to determine whether

boys who participated in Cub Scouts (N = 745) had a greater likelihood that non-Cub Scouts (N = 211) to be members of specific trajectory classes. To address this question, I evaluated whether Cub Scout participants were more or less likely than non-Cub Scouts to be members of the latent class trajectories specified in Research Questions 2 and 3 through pairwise comparisons of proportions. This test of proportions determined the relative odds of membership among Scouts and non-Scouts in each trajectory group.

As shown in Table 23, although the majority of self-perceived academic success trajectory classes did not differ significantly in relative Scout and non-Scout membership, there was one notable difference. Non-Scouts were 2.66 times as likely as Scouts to be members of the "*High, Decreasing*" self-perceived academic success trajectory class as compared to the "*High, Stable*" self-perceived academic success trajectory class (β = .981, p < .05). However, the "*High, Decreasing*" self-perceived academic success trajectory class was relatively small, making up only 18 (8.5%) of 211 non-Scouts, and 38 (5.1%) of 745 Scouts. Therefore, although the difference in odds was significant, the difference only applied to the 344 participants (35.9% of the total sample) in the "*High, Stable*" and "*High, Decreasing*" classes.

I also ran pairwise comparisons of proportions to determine whether Scouting participation was associated with ISOC. Scouts were 3.22 times *less* likely to be in the "*High, Stable*" ISOC trajectory class as compared to the "*Moderate/Low, Stable*" ISOC trajectory class (β = 1.17, p < .05) as shown in Table 24. In addition, Table 24 shows that Scouts were 2.67 times less likely to be in the "*High, Stable*" ISOC trajectory class as compared to the "*Moderate, Stable*" ISOC trajectory class. Last, I ran pairwise comparisons of proportions to determine whether Scouting participation was associated with OSOC. There were no significant

differences in odds ratios between Scouts and non-Scouts with regard to OSOC trajectory classes.

Overall Summary of Results

My analyses resulted in several findings which improved my understanding of ISOC, OSOC, and self-perceived academic success. First, I established that the required reading level for the survey was less than that of the vast majority of participants in the CAMP study. This finding supported the assumption that a typically-literate first grader should be able to read the survey. Next, I determined that the characteristics of the longitudinal sample did not differ from the overall CAMP study sample with regard to age, race, neighborhood characteristics, or socio-economic status to the extent that these differences indicated a sampling bias.

To answer Research Question 1, I established that there were no across-wave differences in ISOC, OSOC, and self-perceived academic success within each grade. In the course of this invariance testing, I determined that Grade 1 participants were significantly different from the other elementary school grades with regard to SOC. Grade 1 participants showed global SOC, as compared to the two-factor model that was found for all other elementary school grades. Next, I was able to establish measurement invariance for ISOC, OSOC, and self-perceived academic success across all remaining grades (i.e., Grades 2 through 5).

To answer Research Question 2, I analyzed a series of Growth Mixture models for self-perceived academic success. I found that a six-trajectory class solution with a quadratic curve was the most appropriate model for self-perceived academic success. To answer Research Question 3, I ran similar GMMs for ISOC and OSOC, and found a three-trajectory class solution was the most appropriate model for ISOC, and a five-trajectory class solution was the most appropriate model for OSOC.

The goal of Research Question 4 was to determine how ISOC and OSOC related to self-perceived academic success trajectory class membership. Therefore, I conducted a series of cross-tabulations and tests of equality of means between ISOC and self-perceived academic success trajectory classes, and OSOC and self-perceived academic success trajectory classes. I found that ISOC and OSOC were significantly related to self-perceived academic success trajectory class membership, with the exception that mean levels of OSOC did not relate to self-perceived academic success trajectory class until Grades 3 through 5.

To answer Research Question 5, I ran a series of analyses to determine whether Cub Scout participation was related to self-perceived academic success trajectory class membership, as well as ISOC trajectory class membership, and OSOC trajectory class membership. These findings were mixed, indicating that Cub Scouts were more likely to be in a "*High, Stable*" self-perceived academic success trajectory class than a "*High, Decreasing*" self-perceived academic success trajectory class. However, I also found that Scouts were more likely to be in "*Moderate/Low, Stable*" ISOC trajectory classes, and "*Moderate, Stable*" ISOC trajectory classes, as compared with "*High, Stable*" ISOC trajectory classes. My discussion of these findings is presented in Chapter 3.

CHAPTER 3: DISCUSSION

This chapter begins with a review of the goals of this dissertation, and a rationale for the methods through which I decided to investigate these research questions. Then, I review the results of my analyses, and discuss the implications and limitations of the findings. Last, I discuss how my findings may inform educational practices, as well as provide suggestions for future research.

Goals of the Dissertation

The primary goal of this dissertation was to explore how intentional self-regulation (ISR) related to self-perceived academic success. In Chapter 1, I reviewed relational developmental systems metatheory, and how the RDS metatheoretical lens can be used as a basis for developing a deeper understanding of processes that contribute to developmental change (Overton, 2013, 2015). RDS metatheory was especially applicable to this investigation because it highlights the development of bidirectional relations between the developing organism and a complex, changing context (Overton, 2013, 2015). When these bidirectional relations, represented as individual ←→ context relations, are mutually beneficial, they may be termed *adaptive* developmental regulations (Brandtstädter, 1998).

The current study was largely focused on intentional self-regulation – part of the individual's role in adaptive developmental regulations, which has been discussed through the Baltes SOC model (Baltes & Baltes, 1990; Freund & Baltes, 2000, 2002). Traditional operationalizations of the SOC construct were differentiated into the three sub-constructs: Selection, Optimization, and Compensation. However, studies during early adolescence (among 10 to 13 year-olds) demonstrated an undifferentiated, global SOC structure (Gestsdóttir & Lerner, 2007; Gestsdóttir et al., 2009). To date, evidence of the developmental level at which

SOC can be expected to differentiate into a tripartite solution is inconclusive (Geldhof et al., 2014).

Despite myriad studies that included the measurement of SOC attributes at several developmental levels, one gap in this life-span assessment of measures was the elementary school grades. Therefore, this dissertation focused on the development of SOC attributes, as well as the outcome of interest, academic success, across the elementary school years. Using data from the Character and Merit Project (CAMP) study (Hilliard et al., in press), Chase (2014) found that this instantiation of the SOC measure used in the CAMP study provided a reliable, psychometrically-sound measure, one sufficient for studying ISR among elementary school-aged participants.

Specifically, Chase (2014) found a two-factor structure (individually- and other-oriented SOC). In addition, preliminary data indicated that both SOC factors predicted self-perceived academic success. However, within the overall CAMP study sample, the relations were stronger between individually-oriented SOC (ISOC) and self-perceived academic success, as compared with other-oriented SOC (OSOC) and self-perceived academic success. The development of ISOC and OSOC, as well as the influence of ISOC and OSOC on self-perceived academic success across the elementary school years, became the focus of this dissertation.

Overview of the Investigation

I began by testing for measurement invariance of self-perceived academic success, ISOC, and OSOC factors across grade in school in the CAMP study data set. Invariance testing was followed by a series of analyses to determine the appropriate number of trajectory classes that best described participants' development of self-perceived academic success, ISOC, and OSOC. After enumerating trajectory classes for self-perceived academic success, ISOC, and OSOC, I

conducted a series of analyses to determine the relations between the predictors (ISOC and OSOC) and the outcome of self-perceived academic success. My analyses concluded with an examination of how other factors (e.g., Cub Scout participation) related to participants' trajectory class membership for self-perceived academic success. Below, I discuss my findings and their implications for educators and educational policy makers.

Discussion of Findings: Research Question 1

To ensure that data could be interpreted meaningfully, I began with several tests of measurement invariance. Before I could test measurement invariance across grade in school, I had to account for possible differences in responses based on the occasion of measurement (wave) for each grade in school. For Grades 2 through 5, I established that there were no across-wave differences in ISOC, OSOC, and self-perceived academic success within each grade. Therefore, I could assume that all participants in a given grade had similar response patterns regardless of the wave in which the data were collected. This finding allowed me to conduct further analyses that organized data by the grade level of each participant, instead of the wave of the CAMP study.

In the course of this across-wave, within grade invariance testing, I found that Grade 1 participants had significant differences from the other elementary school grades with regard to SOC. Upon examination, I found that Grade 1 participants exhibited a global SOC factor structure, as compared to the two-factor model that I identified for all other elementary school grades. I had hypothesized that there might be differences in conceptualization of SOC among elementary school aged students, although I did not have any theory-predicated notion of the developmental level in which such a change would occur. One possibility for the global SOC structure among Grade 1 participants could be a lack of nuanced comprehension of the items,

due to their limited reading comprehension skills. Another explanation for the changes from a more global structure of SOC in Grade 1 to a more differentiated factor structure in Grades 2 through 5 may be the orthogenetic principle. The orthogenetic principle explains that behavioral processes tend to move from a more general, global state in earlier developmental periods to a more differentiated structure as an individual develops (Werner, 1957). Therefore, such differentiation from one to two factors of SOC through the elementary school years would fit Werner's characterization of a differentiated behavioral process.

Next, I was able to establish measurement invariance for ISOC, OSOC, and self-perceived academic success across Grades 2 through 5 (due to the difference in SOC structure, I omitted Grade 1 participants from subsequent analyses). Establishing configural, loading, and intercept invariance was a key finding because it allowed me to assume that the interpretation of mean scores and factor loadings for each grade were equivalent. Therefore, these factors demonstrated continuity over time such that changes in ISOC, OSOC, or self-perceived academic success in Grade 2 could be considered equivalent to changes in these same constructs in Grade 4 (Lerner, 2002). In addition to establishing measurement equivalence, measurement invariance across grades allowed me to analyze the data across grade in school. This step was important because grade in school was a more meaningful unit of analysis than analyzing data by wave for the questions I wanted to address in subsequent analyses, that is, questions regarding interindividual differences in intraindividual change in intentional self-regulation and self-perceived academic success across the elementary school years.

Discussion of Findings: Research Question 2

To answer Research Question 2, I analyzed a series of growth mixture models for self-perceived academic success. I found that a six-trajectory class solution with a quadratic curve

was the most appropriate model for self-perceived academic success. The six-factor model of self-perceived academic success was an informative finding on its own, as it provided a nuanced description of the heterogeneity of trajectories of self-perceived academic success across the elementary school years. Although the trajectories were heterogeneous, 87.3% of participants fell into one of three stable trajectory classes (as shown in Figure 3), indicating that many boys in the CAMP study had relatively stable perceptions of their success in school across the elementary school years. However, these self-perceptions varied widely with regard to mean levels across the three stable trajectory classes. This wide variety of intercepts and slopes exemplified the need for GMMs to model self-perceived academic success, instead of a more traditional latent growth curve model.

In addition to the findings of stable classes highlighted above, there were also examples of "changer" self-perceived academic success trajectory classes, which resulted in examples of both equifinality and multifinality. Multifinality was demonstrated by the "*High, Decreasing*" trajectory class, which began with a very similar intercept as the "*High, Stable*" trajectory class at Grade 2, but had decreased dramatically by Grade 5. Conversely, equifinality was demonstrated by the "*Low, Increasing*" trajectory class. This "*Low, Increasing*" trajectory class began with low levels of self-perceived academic success, but increased to similar levels of self-perceived academic success as the "*High, Stable*" trajectory class by Grade 5. These examples of multifinality and equifinality became particularly informative when predictors such as Cub Scout participation were found to relate to self-perceived academic success trajectory class membership, as I discuss in greater detail in my discussion of findings regarding Research Question 5.

Discussion of Findings: Research Question 3

To answer Research Question 3, I conducted a series of GMMs for ISOC and OSOC to determine the most appropriate number of trajectory classes for each construct. For ISOC, I found a three-trajectory class solution was the most appropriate model. The three trajectory classes for ISOC were quite stable in regard to their Grade 2 and Grade 5 intercepts (i.e., the "*High, Stable*", "*Moderate, Stable*", and "*Low, Moderate, Low*" ISOC classes began and ended at the same mean level). However, I labeled the "*Low, Moderate, Low*" trajectory class as a changer, as the ISOC levels increased to moderate levels at Grades 3 and 4, overlapping with the *"Moderate, Stable*" trajectory class. This unusual trajectory was somewhat difficult to interpret, and most likely contributed to the mediocre entropy in the ISOC measurement model. However, despite the overlapping of otherwise-stable trajectory classes at Grades 3 and 4, trajectory class membership proved to be a useful model of ISOC in relation to the outcome of interest (i.e., self-perceived academic success), as I explain below in my discussion of findings from Research Question 4.

The second aspect of Research Question 3 was to determine the optimal trajectory-class solution for OSOC. As displayed in Figure 5, the most appropriate OSOC model was a five-trajectory class solution, which included three stable trajectory classes (i.e., "*High, Stable*," "*Moderate/High, Stable*," and "*Moderate, Stable"*), and two "changer" trajectory classes (i.e., "*High, Low, Moderate/High*", and "*Low, Moderate, Low*"). As with the changer trajectory class in the ISOC model, both of the changer trajectory classes in the OSOC model were characterized by quadratic curves that caused them to overlap with other trajectory classes in the middle grades (i.e., Grades 3 and 4). Indeed, the "*High, Low, Moderate/High*" trajectory class intersected with each of the four other trajectory classes over the course of the elementary school years.

However, this "*High, Low, Moderate/High*" trajectory class had only 31 members (i.e., 3.2% of the total sample); therefore, the vast majority of participants did not experience such non-linear change in OSOC over the elementary school years. This trajectory class could also be explained by the fact that, as a result of design-based missingness, the sample is not longitudinal across all grades. That is, any single participant could only have participated in a total of two or three grades (those who participated in only one grade were not included in my analyses). Therefore, the "*High, Low, Moderate/High*" trajectory class could be representative of participants in Grades 2 and 3 (and potentially Grade 4) who decreased in OSOC, and participants in Grades 4 and 5 who increased in OSOC. Thus, what appears to be a quadratic slope may, potentially, represent participants in two linear slopes at different points in elementary school. This interpretation may be relevant to several of the changer trajectory classes identified in other GMMs as well, such as the *"Low, Moderate, Low"* ISOC trajectory class. However, further analysis of these changer trajectory classes must be completed before any conclusions can be drawn.

Discussion of Findings: Research Question 4

Research Question 4 addressed the main focus of my dissertation – to determine how ISOC and OSOC related to self-perceived academic success, as indexed by self-perceived academic success trajectory class membership. To answer this question, I conducted a series of cross-tabulations, as well as tests of equality of means, between ISOC and self-perceived academic success trajectory classes. I conducted the same analyses between OSOC and self-perceived academic success trajectory classes. I found that ISOC and OSOC were significantly related to self-perceived academic success trajectory class membership, with the exception that mean levels of OSOC did not relate to self-perceived academic success trajectory class until

Grades 3 through 5. These findings were theoretically meaningful because they answered a key question: Are intentional self-regulation attributes, as operationalized by ISOC and OSOC, related to self-perceived academic success in general? In both of the cross-tabulation analyses, as well as the tests of equality of means, I confirmed that in fact, SOC factors did relate to self-perceived academic success, but at different times, and to different degrees, as discussed below.

There were several nuances of the findings that are worthy of note. First, tests of equality of means found that OSOC mean scores were not related to self-perceived academic success trajectory classes at Grade 2. Therefore, although OSOC was associated with overall self-perceived academic success trajectory class membership, as demonstrated in the cross-tabulation analyses displayed in Table 18, these relations were not significant until later in elementary school, as shown in Tables 19 through 22. This finding was inconsistent with one of my initial hypotheses, as I had posited that students would require OSOC attributes to succeed early in their elementary school careers when directed-teaching was more common, as compared to later in elementary school when independent learning tasks became more vital to academic success. The rationale for my hypothesis was that direct teaching required more interaction with the teacher; thus, the help-seeking abilities that characterize OSOC should have been particularly relevant in these early elementary school years.

A possible explanation for my failure to predict the timing of the relevance of OSOC attributes is that I focused on a relevant example, but came to the wrong conclusion. Specifically, students in early elementary school are learning discrete skills which may not require the student to take initiative and seek out help from a teacher. In contrast, although self-guided learning activities and homework certainly require a student to regulate his or her own actions through hard work and developing new strategies during these independent activities (i.e., characteristics

of ISOC), it may be equally important to seek help from others and have the ability to garner resources when confronted with a problem (i.e., characteristics of OSOC). After all, independent projects, or more generally, projects and homework not characterized by direct instruction, do not put students in isolation. They often require teamwork with classmates, and drawing upon resources provided by teachers, parents, and siblings to complete the task. This situation may explain why the ability to seek out resources became even more important in the later elementary school years, as work becomes more complex, and students are given more autonomy to complete the tasks.

Although my original hypothesis may have been incorrect regarding the relative influence of the two SOC variables at different elementary school grades, I was correct about the timing of a shift in relevance of intentional self-regulation attributes in later elementary school grades, beginning at Grades 3 and 4, as shown in Tables 14 through 17 (ISOC), and Tables 19 through 22 (OSOC). Although expectations of literacy (and, as a result, curricula) vary across educational systems in the United States, one commonality is that students in later elementary school grades are asked to build upon previous learning and complete more complicated tasks, as noted above (Montague, 2007). By Grades 3 and 4, as explained in Chapter 1, many students are expected to begin a transition from “learning to read” to “reading to learn.” Although this shift in reading tasks may be an oversimplification of the learning process, there is little debate that students are expected to apply their literacy skills to a greater extent in the later elementary school years (Chall & Jacobs, 2003; Chall et al., 2009).

Therefore, by Grades 3 and 4, intentional self-regulation skills begin to relate to self-perceived academic success to an even greater extent, as more complicated tasks require attributes such as sustained attention and persistent effort (Fantuzzo, Gadsden, & McDermott,

2008, 2011) and the ability to draw from individual and contextual resources (Gestsdóttir & Lerner, 2008). As explained in Chapter 2, the number of self-perceived academic success trajectory classes that were significantly different from one another with regard to mean levels of ISOC increased in later grades. In addition, the effect size was greatest at Grade 5, indicating even stronger relations between ISOC and self-perceived academic success. In turn, OSOC did not predict self-perceived academic success at Grade 2, but remained a consistent (though relatively weak) predictor of self-perceived academic success trajectory class across Grades 3 through 5. Both of these findings support the notion that intentional self-regulation skills become more salient as students progress through the elementary school years.

Discussion of Findings: Research Question 5

To answer Research Question 5, I ran a series of analyses to determine whether Cub Scout participation was related to self-perceived academic success trajectory class membership, as well as ISOC trajectory class membership and OSOC trajectory class membership. These findings were mixed, indicating that Cub Scouts were more likely to be in a "*High, Stable*" self-perceived academic success trajectory class than a "*High, Decreasing*" self-perceived academic success trajectory class. However, I also found that Scouts were more likely to be in "*Moderate/Low, Stable*" ISOC trajectory classes, and "*Moderate, Stable*" ISOC trajectory classes, as compared with "*High, Stable*" ISOC trajectory classes. This finding seems counterintuitive, because, based on the findings from Research Question 4, intentional self-regulation skills and self-perceived academic success were found to be nearly universally related.

The relation of Scouting participation to self-perceived academic success provided some support for previous findings that Scouting participation may promote academic success (Hershberg et al., under review). However, my *a priori* expectation was that Scouting would

also contribute to ISOC and OSOC, which then contributed to higher levels of self-perceived academic success, for programmatic reasons I explain below. In addition to this mediation effect, I expected aspects of the Scouting program other than those that promoted SOC attributes (i.e., skill-building activities) to have direct effects on self-perceived academic success. This expectation was based on qualitative analyses of interview data which supported the conclusion that Scouting promoted persistence, teamwork, and experiential learning, and that these skills may have contributed to academic achievement (Hershberg et al., under review). However, as explained above, only direct effects on self-perceived academic success were found. To my surprise, Cub Scout participants were actually less likely to be members of the "*High, Stable*" ISOC trajectory class than non-Scouts.

The above, mixed findings may be explained by noting the differences between the Cub Scout program, and the Boy Scout program. Although the overall mission of Scouting includes a leadership component, and places great emphasis on building agentic, goal-oriented, self-sufficient individuals, Scouting does not focus on the individual challenges that explicitly engender these qualities, such as working toward a merit badge on one's own, and pursuing leadership opportunities, until boys enter the Boy Scout program in Grade 6. The Cub Scout program, however, does include a wide variety of skill building activities and teamwork. For example, Cub Scouting activities encourage participants to apply academic skills in real-life situations, such as the use of reading and mathematics for following directions, measuring, and building model rockets (BSA website: http://www.scouting.org).

One possible explanation, then, for the seemingly mixed findings regarding Cub Scout participation's relations with self-perceived academic success is that the many enrichment activities in the Cub Scouting program may have contributed to self-perceived academic

achievement. However, intentional self-regulation skills, especially the individually-oriented skills that are part of the mission of the Boy Scouts of America, may not be influenced until later in the BSA program. Therefore, continued analysis of Cub Scouts as they "cross-over" into Boy Scouts in later years may be informative, as the more explicit emphasis on goal pursuit strategies characterized by the Boy Scout program may relate to self-regulation attributes, as well as academic success. Such an exploration of the impact of out-of-school-time (OST) programs that promote self-regulation attributes may also inform best practices in schools and OST programs, as explored in previous studies (Bowers, et al., in press; Napolitano et al., 2014).

Limitations

The present findings have several limitations that must be noted. The first limitations are related to the CAMP study sample, which was not nationally representative, as all participants were residents of the greater Philadelphia area. The sample was, however, characteristic of the socio-economic, rural-urban, and racial/ethnic diversity of the region in which the study took place.

In addition, the sample was all male, due to the fact that a primary goal of the CAMP study was to assess youth who participated in the Cub Scout program (Hilliard et al., in press). Naturally, participants were also more likely to participate in the Scouting program than the average elementary school student (78.0% of the longitudinal sample participated in Scouts), which further limited the generalizability of these findings.

Therefore, although many of the results of this study may be generalizable across gender, region, and youth development program affiliation in the United States, caution dictates that my findings be replicated with other populations before such generalizations can be made. However, as explained by Duckworth and Seligman (2006), boys are more likely than girls to

have problems with academic success as a result of failure to demonstrate ISR attributes. Therefore, despite the limitation that this study did not include girls, the target population of this study (boys) may have the greatest need for ISR-oriented education and interventions. Nevertheless, future studies must include girls to determine whether the results of the current study are replicable across gender.

Another limitation of this study is the item pool used to measure ISOC, OSOC, and self-perceived academic success. Ideally, when conducting research with latent constructs, each factor should be represented by at least three items (Little, 2013). However, the model of SOC that I identified (Chase, 2014) had a four-item factor (ISOC) and a two-item factor (OSOC). Model fit was quite strong for the two-factor model of ISOC and OSOC; however, this item set provided an impoverished measure of OSOC. In contrast, the self-perceived academic success measure met the minimum suggested number of items for a factor, and demonstrated good model fit; but it is possible that additional aspects of self-perceived academic success existed that were not measured by these three items. Therefore, a larger item pool for self-perceived academic success could have been useful. The limited item pool was necessary, however, due to the young age (and, therefore, relatively short attention spans) of participants in the CAMP study – many as young as six years old. Future studies of older youth may benefit from the inclusion of more SOC and self-perceived academic success items, which would allow for more, and improved, analyses of the two-factor model of SOC. In addition, more objective measures of academic success could be included to augment the self-report data, and mitigate any self-report bias.

Another key measurement limitation had to do with the design of the longitudinal sample. Although a grade-based longitudinal sample provided much more readily interpretable findings, an unfortunate result was that participants had fewer occasions of measurement as a result, and

some data were not able to be used. For example, students who began the study at Grades 4 and 5 “aged out” of the grades that were relevant to this study. Although the CAMP study continued to follow many of these participants into the middle school years, I was unable to use these data for my elementary school analyses as a result of this “aging out” situation.

Similarly, participants who became old enough to join the CAMP study at later waves were not recruited as deliberately as at the beginning of the study, because the top priority was to maintain the longitudinal sample. Therefore, there were fewer new Grade 1 students in later waves and, subsequently, fewer Grade 1 students in the longitudinal sample overall. As a result of the two design-based issues with regard to grade in school, the sample had more longitudinal participants in the middle grades, and fewer participants at Grades 1 and 5. Yet, there were still sufficient longitudinal participants in each grade for the analyses presented. Further analyses of sub-groups within the longitudinal sample may have been possible, however, had the study been more equally and fully representative across the elementary school grades.

My decision to merge the data into a single score for each grade was a difficult one, but necessary, as a result of the design-based missingness explained above. As explained in Chapter 2, longitudinal measurement across multiple occasions in each grade would have provided a more nuanced set of analyses. Some additional analyses could have provided a deeper understanding of the processes that occur throughout the year. For example, it is possible that participants had more optimistic perceptions of their academic success in the spring, having mastered the material of that school year. In contrast, many students return to school in the fall, having suffered a “summer-slump” (Bottorff, 2010), a negative experience that could lead to a negative academic self-concept. Not only would such differences in spring and fall responses have been a noteworthy finding, but the inability to detect such changes in the current

investigation is a possible source of bias in my analyses. Fortunately, the relatively large sample size helped to mitigate this potential bias.

Next Steps

As addressed earlier in this chapter, Cub Scout participation had a modest, positive positively relation to self-perceived academic success. This relation supported findings from Hershberg et al. (under review) which, also using data from the CAMP study, suggested that Scouting may contribute to academic success. However, Scouting was a dichotomous variable in these analyses, such that participants were labeled “In Cub Scouts” or “Not in Cub Scouts.” As such, I did not have the opportunity to analyze subgroups of Cub Scouts, such as those who participated in the Cub Scout program more often (i.e., frequency and intensity of participation), and participants who had been Cub Scouts for several years (i.e., duration of participation). Therefore, these issues of possible dosage effects of Scouting may be a factor to consider in future research to gain a more nuanced understanding of Scouting’s influences on academic success. If specific *levels* of Scouting participation are associated with the development of SOC and/or self-perceived academic success, then the Scouting program could recommend levels of participation accordingly.

In regard to my ad hoc hypothesis that Scouting may not contribute to intentional self-regulation attributes until Boy Scouts, a future study could also use mixed methods to provide an in-depth investigation of whether Boy Scout programs promote intentional self-regulation attributes and academic success. Such an analysis could be conducted using interviews from the CAMP study and continued research into the Boy Scout years to determine individual differences and similarities with regard to goal pursuit and other SOC-related strategies. Such interview findings, paired with quantitative data from these interviewees (i.e., measures of SOC

and self-perceived academic success), may be used in a future study to analyze how youth at varied points in the development of SOC attributes conceptualize their own self-regulatory behaviors.

However, as I addressed in the Limitations section, future studies may benefit from the inclusion of more SOC items, which would allow for more, and improved analyses of the two-factor model of SOC. As explained in Chapter 2, EFAs conducted by Geldhof and colleagues (2014), using SOC data from the 4-H Study of PYD (Lerner et al., 2005), found similar response patterns as the Chase (2014) model, but with a larger item pool. Based on the findings from the current investigation, Chase (2014), and Geldhof et al. (2014), an age appropriate, adapted version of these items should be developed in future studies. This larger item pool may provide a more psychometrically sound measure of SOC among elementary school-aged youth, and beyond.

RDS metatheory encourages the use of change-sensitive methodologies to gain a more complete understanding of development (Overton & Lerner, 2014). One of the benefits of using GMM in my analyses was the ability to take into account interindividual differences in intraindividual change by addressing the often-ignored fact that not all youth develop in the same way, or at the same time. Although there must always be a balance between conducting generalizable, interpretable analyses and considering sub-group and individual levels of variation, GMM provided an interpretable, yet nuanced method for modeling self-perceived academic success, ISOC, and OSOC across the elementary school years that accurately reflected the individual variation in trajectories of CAMP study participants.

Based on the finding that intentional self-regulation, particularly as operationalized by ISOC, was related to self-perceived academic success across the elementary school years, future

studies should attempt to determine the processes through which elementary school aged youth develop intentional self-regulation attributes. Educators in particular, based on the findings of this dissertation, may benefit from determining what educational practices may contribute to the development of intentional self-regulation attributes in a school-specific context. For example, projects that promote agency, teamwork, and feelings of accomplishment may encourage elementary school aged students to pursue their goals.

Recommendations for Policy and Practice

There is an old expression, the origins of which are widely debated: "Give a man a fish, and you feed him for a day; teach him how to fish, and you feed him for a lifetime." Despite the ubiquity of this sentiment, the lesson does not always reflect the type of education that children experience in the United States. Of course, children learn many useful skills in school, and these skills may benefit them in their academic careers, as well as their eventual professional careers. However, in this analogy, I use "fishing" not as the set of academic skills that students learn, but as the tools for learning. The results of the current investigation indicated that the most academically successful children were those who were able to regulate their own actions, focus their efforts meaningfully, and capitalize on contextual resources to pursue their goals. Therefore, educators and policy makers should consider the implementation of methods that promote the development of intentional self-regulation skills in academic curricula (Heckman, 2008).

In Chapter 1, I described several successfully educational programs with the goal of improving self-regulation attributes among students, such as the Tools of the Mind program (Wilson & Farran, 2012) and the Evidence-Based Program for Integrated Curricula (EPIC; Fantuzzo, et al., 2011). Many school programs encourage these same attributes through the

framework of Social Emotional Learning (SEL), a construct which includes many of the same characteristics as intentional-self regulation skills (e.g., help-seeking, setting positive, realistic goals, and emotion regulation; Elias, 2004). A meta-analysis of SEL interventions demonstrated that these and other key SEL attributes could be improved, and that this improvement in SEL attributes was associated with significant gains in academic success (Durlak, Weissberg, Dymnicki, Taylor, & Schellinger, 2011).

An additional concept that may contribute to teaching methods as well as educational policy is the concept of teaching from the growth mindset perspective by rewarding behaviors and attitudes that demonstrate willingness to work hard toward an academic goal (Dweck, 1999). Dweck contrasted the growth mindset approach with the fixed mindset approach, which is based on the implication that students succeed because of their "innate" levels of academic skill, or intelligence.

Students in classrooms that promoted a growth mindset had greater academic outcomes than students in the fixed mindset classrooms (Dweck, 2006). As Dweck (2006) explained, teachers promoted the assumption that a students' success was a result of hard work. Students were encouraged by this sense of empowerment and control (i.e., agency) in relation to their own academic destinies, and responded by working even harder as a result of their early successes (Dweck, 2006). In contrast, students in the fixed mindset classrooms felt that their academic outcomes were inevitable, and, therefore, studied far less than their growth-minded counterparts. In fact, many students in the fixed mindset classrooms interpreted hard work by their classmates as a sign of limited ability (Dweck, 2006). Even students who were told that they were gifted or talented in specific subject areas were negatively affected by the fixed-mindset condition, ostensibly because they were not given the motivation to work harder to meet their ultimate

potential. Dweck's (2006) study is an important lesson for educators because all students will eventually meet adversity, no matter their academic prowess. Students who have a growth-mindset, and are imbued with the self-regulatory attributes to maximize their efforts, may have the greatest likelihood of academic success.

Although teachers can certainly encourage self-regulation strategies and a growth mindset simply through their word choice and attitudes toward academic success (i.e., through hard work, effort, and study habits), there are more concrete steps that can be taken to promote self-regulation strategies as well. Many teachers insist that students show their work as compared to simply showing the final answer, to demonstrate that, not only have students mastered the material, but that the students put in the effort to solve the problem, and understood each step in the process. By rewarding behaviors such as effort, participation, and homework in students' evaluations, teachers send a clear message that effort, as exemplified by intentional self-regulation attributes and growth mindset, matters. To encourage the aspects of intentional self-regulation characterized by other-oriented SOC, teachers should have a similarly encouraging attitude toward students who ask questions, or make creative use of resources to accomplish academic tasks.

In addition to changing the rewards system, intentional self-regulation attributes could be promoted through relevant teaching practices. For example, portfolio-based assessment may contribute to this goal in several ways (Barrett, 2007; Wiley & Haertel, 1996). In this type of assessment, teachers record student work in portfolios to help identify students' individual strengths and weaknesses, and give them a chance to provide input into their own learning process. Using portfolio-based assessments, including electronic portfolios, would allow students to attempt new strategies, engage in self-reflection, and apply new skills – as well as

provide students with a natural opportunity to seek out help from the teacher by discussing strategies that may assist students in improving their portfolio projects (Barrett, 2007; Wiley & Haertel, 1996). The portfolio represents a concrete, tangible product that teaches intentional self-regulation attributes.

Unfortunately, many educators have been pushed away from portfolio-based assessments and similar teaching practices that reward the effort and resourcefulness of students. Instead, educators are pushed further toward a model of "teaching to the test" – a system that only rewards performance on a single, standardized exam that students are given at the end of a school year (Pavia, 2012). The pressures on teachers to prepare students for high-stakes tests comes from principals, school districts, and state level interests, and may have the unfortunate result of discouraging creative and innovative educational practices (Pavia, 2012). Policy makers should consider the impact of the ubiquity of high-stakes standardized testing on the development of agency and motivation among students.

Conclusions

The individual undeniably plays an active role in his or her development, and yet, "no man is an island" (Donne, 1839). Donne's assertion is as relevant now as it was in years past, that all individuals are all connected, and that, as he wrote, "every man is a piece of the continent." From a RDS metatheory perspective, one could interpret Donne's poem to mean that no individual can thrive without others. By implementing adaptive developmental regulations that allow him or her to simultaneously gain from, and contribute to, his or her context, both the individual and the context may thrive.

The two-factor model of SOC served as an operationalization of concepts of RDS metatheory, most notably the bidirectional influences that characterize development in a social

world. Through this investigation, I sought to expand upon previous understanding of the development of ISR attributes and their relations with academic success, particularly among the oft-overlooked developmental level of elementary school-aged youth. Intentional self-regulation attributes that help individuals garner contextual resources to achieve their goals, as well as intentional self-regulation attributes that individuals call upon to help themselves, are paramount in the pursuit of academic success.

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Table 1. Latent correlations of OSOC, ISOC, and self-perceived academic success across Waves 1 through 4 of the CAMP study.

	1	2	3	4	5	6	7	8	9	10	11	12
1. W1OSOC	1.00											
2. W2OSOC	0.50*	1.00										
3. W3OSOC	0.40*	0.38*	1.00									
4. W4OSOC	0.39*	0.46*	0.55*	1.00								
5. W1ISOC	0.59*	0.30*	0.39*	0.33*	1.00							
6. W2ISOC	0.28*	0.53*	0.30*	0.37*	0.65*	1.00						
7. W3ISOC	0.17*	0.26*	0.50*	0.30*	0.61*	0.73*	1.00					
8. W4ISOC	0.20*	0.27*	0.41*	0.62*	0.51*	0.59*	0.74*	1.00				
9. W1ACSC	0.23*	0.14*	0.17*	0.11*	0.59*	0.37*	0.40*	0.39*	1.00			
10. W2ACSC	0.17*	0.26*	0.23*	0.21*	0.45*	0.67*	0.54*	0.48*	0.78*	1.00		
11. W3ACSC	0.03	0.14*	0.23*	0.16*	0.28*	0.40*	0.63*	0.48*	0.68*	0.84*	1.00	
12. W4ACSC	0.10	0.19*	0.23*	0.31*	0.32*	0.36*	0.53*	0.73*	0.60*	0.64*	0.83*	1.00

Note: * $p < .05$. *OSOC* = Other-oriented SOC. *ISOC* = Individually-oriented SOC. *ACSC* = Self-Perceived Academic Success. *W1* = Wave 1, *W2* = Wave 2, *W3* = Wave 3, *W4* = Wave 4. Solid right triangles indicate auto-regressive correlations. Dotted rectangle indicates *ISOC* correlating with *OSOC*. Solid rectangle indicates *OSOC* correlating with *ACSC*. Dashed rectangle indicates *ISOC* correlating with *ACSC* (from Chase, 2014).

Table 2. Number of participants in Grades 2 through 5 in the half-grade model, compared with the full-grade model, and pattern of participation by full-grade.

Cross Grade – Half-Grade Participants

	Grade 2	Grade 2.5	Grade 3	Grade 3.5	Grade 4	Grade 4.5	Grade 5	Grade 5.5
Schl1	247	331	498	441	559	441	403	189
Schl3	242	328	503	446	562	444	404	194
Schl4	240	325	492	430	559	440	401	192
SOC01	243	322	501	437	559	438	402	194
SOC02	248	326	494	447	565	442	401	197
SOC03	244	325	486	435	552	438	403	193
SOC04	247	325	502	442	565	442	403	196
SOC05	246	330	506	444	565	442	405	197
SOC06	244	323	493	438	562	440	402	190

***Note*: Among non-Scouts – ranged from 57-127.**

Cross Grade – Full Grade Participants

	Grade 2	Grade 2.5	Grade 3	Grade 3.5	Grade 4	Grade 4.5	Grade 5	Grade 5.5
Schl1	377	n/a	660	n/a	718	n/a	450	n/a
Schl3	374	n/a	665	n/a	717	n/a	454	n/a
Schl4	371	n/a	658	n/a	714	n/a	452	n/a
SOC01	369	n/a	664	n/a	715	n/a	454	n/a
SOC02	372	n/a	662	n/a	719	n/a	452	n/a
SOC03	367	n/a	657	n/a	714	n/a	449	n/a
SOC04	371	n/a	664	n/a	718	n/a	451	n/a
SOC05	375	n/a	669	n/a	719	n/a	454	n/a
SOC06	365	n/a	659	n/a	717	n/a	447	n/a

Pattern of Participation across Grades 2 through 5

Grade	N	Percentage
0011	276	28.8
0101	10	1.0
0110	125	13.0
0111	169	17.6
1010	10	1.0
1100	225	23.5
1110	144	15.0
Total	959	100%

Note: The "Grade" column indicates the grades in school in which a participant took the survey. For example, a participant in the 1110 category participated during Grades 2, 3, and 4, but not in Grade 5.

Table 3. Fit indices for across-wave, within-grade measurement invariance testing at Grade 1.

Model	$\chi 2$	*df*	*p*	$\Delta\chi 2$	Δ *df*	RMSEA	CFI	Δ CFI	TLI
Configural Model (Two factors)	73.78	62	<.01	---	---	0.071	0.945	---	0.914
Loading Invariance Model	94.20	57	<.01	20.42	-5	0.073	0.926	0.019*	0.907
Configural Model (One factor)	77.44	50	<.01	---	---	0.067	0.946	---	0.922
Loading Invariance Model	86.81	56	<.01	9.37	6	0.067	0.939	0.007	0.921
Intercept Invariance Model	96.60	65	<.01	19.16	15	0.063	0.937	0.009	0.931

Note: * = significant change in CFI, indicating non-invariance. RMSEA = Root Mean Square Error Approximation; CI = 90% Confidence Interval; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index;

Table 4. Fit indices for across-wave, within-grade measurement invariance testing at Grade 2.

Model	$\chi 2$	*df*	*p*	$\Delta\chi 2$	Δ *df*	RMSEA	CFI	Δ CFI	TLI
Configural Model (Two factors)	107.08	48	<.001	---	---	0.068	0.945	---	0.918
Loading Invariance Model	118.29	57	<.01	11.21	9	0.064	0.943	0.002	0.928
Intercept Invariance Model	133.90	66	<.01	19.16	18	0.062	0.937	0.008	0.931

Note: RMSEA = Root Mean Square Error Approximation; CI = 90% Confidence Interval; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index;

Table 5. Fit indices for across-wave, within-grade measurement invariance testing at Grade 3.

Model	$\chi 2$	*df*	*p*	$\Delta\chi 2$	Δ *df*	RMSEA	CFI	Δ CFI	TLI
Configural Model (Two factors)	116.52	48	<.001	---	---	0.068	0.955	---	0.932
Loading Invariance Model	128.33	57	<.001	11.81	9	0.063	0.953	0.002	0.941
Intercept Invariance Model	141.54	66	<.001	25.02	18	0.061	0.950	0.005	0.946

Note: RMSEA = Root Mean Square Error Approximation; CI = 90% Confidence Interval; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index;

Table 6. Fit indices for across-wave, within-grade measurement invariance testing at Grade 4.

Model	$\chi 2$	*df*	*p*	$\Delta\chi 2$	Δ *df*	RMSEA	CFI	Δ CFI	TLI
Configural Model (Two factors)	78.44	48	<.01	---	---	0.041	0.982	---	0.973
Loading Invariance Model	98.37	57	<.001	19.93	9	0.043	0.976	0.006	0.970
Intercept Invariance Model	108.65	66	<.001	30.21	18	0.050	0.975	0.007	0.973

Note: RMSEA = Root Mean Square Error Approximation; CI = 90% Confidence Interval; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index;

Table 7. Fit indices for across-wave, within-grade measurement invariance testing at Grade 5.

Model	$\chi 2$	*df*	*p*	$\Delta\chi 2$	Δ *df*	RMSEA	CFI	Δ CFI	TLI
Configural Model (Two factors)	78.44	48	<.01	---	---	0.041	0.982	---	0.973
Loading Invariance Model	98.37	57	<.001	19.93	9	0.043	0.976	0.006	0.970
Intercept Invariance Model	108.65	66	<.001	30.21	18	0.050	0.975	0.007	0.973

Note: RMSEA = Root Mean Square Error Approximation; CI = 90% Confidence Interval; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index;

Table 8. Fit indices for across-grade measurement invariance across Grades 2 through 4.

Model	$\chi 2$	*df*	*p*	$\Delta\chi 2$	Δ *df*	RMSEA	CFI	Δ CFI	TLI
Configural Invariance Model	389.03	261	<.001	---	---	0.023	0.965	---	0.952
Loading Invariance Model	397.73	267	<.001	8.70	8	0.023	0.964	0.001	0.953
Intercept Invariance Model	449.44	297	<.001	60.41	36	0.023	0.958	0.007	0.950

Note: RMSEA = Root Mean Square Error Approximation; CI = 90% Confidence Interval; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index;

Table 9. Fit indices for across-grade measurement invariance across Grades 4 through 5.

Model	$\chi 2$	*df*	*p*	$\Delta\chi 2$	Δ *df*	RMSEA	CFI	Δ CFI	TLI
Configural Invariance Model	181.50	111	<.001	---	---	0.029	0.974	---	0.965
Loading Invariance Model	195.88	120	<.001	14.38	9	0.029	0.972	0.002	0.965
Intercept Invariance Model	210.29	129	<.001	28.79	18	0.029	0.970	0.004	0.965

Note: RMSEA = Root Mean Square Error Approximation; CI = 90% Confidence Interval; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index;

Table 10. Results for the growth mixture modeling trajectory classes of self-perceived academic success.

Profiles	AIC	BIC	Entropy	LMR (*p*-value)	BLRT (*p*-value)	*N* members per class
1	4295.807	4344.466	n/a	n/a	n/a	959
2	4241.232	4323.952	0.495	n/a	n/a	259, 700
3	4134.143	4231.460	0.580	n/a	n/a	310, 405, 244
4	4084.273	4210.786	0.589	0.0053	0.0000	276, 190, 94, 399
5	4176.606	4288.521	0.774	0.0520	0.0000	275, 13, 60, 344, 267
6[1]	**4134.779**	**4266.158**	**0.777**	**0.0883**	**0.0000**	**56, 400, 288, 14, 51, 150**
7	4107.997*	4258.839	0.776	0.0666	0.0000*	48, 117, 285, 9, 49, 398, 53

Note: [1] indicates the chosen factor solution. * Indicates a failure of convergence, making the estimate unreliable.
AIC = Akaike Information Criteria; BIC= Bayesian information criterion; LMR (*p*-value) = *p*-value for the Lo-Mendel-Rubin test; BLRT (*p*-value) = *p*-value for the Bootstrapped Likelihood Ratio Test.

Table 11. Results for the growth mixture modeling trajectories of individually-oriented SOC (ISOC).

Profiles	AIC	BIC	Entropy	LMR (*p*-value)	BLRT (*p*-value)	*N* members per class
1	4776.319	4824.978	n/a	n/a	n/a	959
2	4764.879	4828.135	0.530	n/a	n/a	910, 49
3[1]	**4707.324**	**4790.044**	**0.596**	**0.1189**	**0.0000**	**568, 225, 166**
4	4705.098	4807.282	0.660	0.1124	0.0000	152, 6, 550, 251
5	4682.172	4808.685	0.561	0.2379	0.0000*	21, 261, 98, 101, 478
6	4687.190	4818.569	0.678	0.1750	0.0000*	206, 26, 354, 276, 45, 52
7	4674.693	4825.535	0.689	0.0300	0.0000*	333, 27, 182, 274, 61, 64, 18

Note: [1] indicates the chosen factor solution. * Indicates a failure of convergence, making the estimate unreliable.
AIC = Akaike Information Criteria; BIC= Bayesian information criterion; LMR (*p*-value) = *p*-value for the Lo-Mendel-Rubin test; BLRT (*p*-value) = *p*-value for the Bootstrapped Likelihood Ratio Test.

Table 12. Results for the growth mixture modeling trajectories of other-oriented SOC (OSOC).

Profiles	AIC	BIC	Entropy	LMR (*p*-value)	BLRT (*p*-value)	*N* members per class
1	6024.653	6073.312	n/a	n/a	n/a	959
2	5903.094	5976.083	0.513	n/a	n/a	498, 461
3	5794.878	5882.464	0.630	n/a	0.0000	403, 397, 159
4	5787.937	5890.121	0.669	0.1174	0.0000	97, 168, 279, 415
5[1]	**5748.483**	**5879.862**	**0.693**	**0.0162**	**0.0000**	**400, 134, 161, 31, 233**
6	5767.399	5898.778	0.766	0.1353	0.0000	406, 238, 168, 51, 25, 71

Note: [1] indicates the chosen factor solution. * Indicates a failure of convergence, making the estimate unreliable.
AIC = Akaike Information Criteria; BIC= Bayesian information criterion; LMR (*p*-value) = *p*-value for the Lo-Mendel-Rubin test; BLRT (*p*-value) = *p*-value for the Bootstrapped Likelihood Ratio Test.

Table 13. Cross-tabulation of ISOC trajectory class membership and self-perceived academic success class membership.

ISOC Class	Academic Success Class	High, Decreasing	Moderate/High, Stable	High, Stable	Moderate, Decreasing	Moderate, Stable	Low, Increasing to High
Low/Moderate, Stable	Count:	33	276	134	6	85	34
	Expected:	33.2	236.9	170.6	8.3	88.8	30.2
High, Stable	Count:	10	59	130	1	19	6
	Expected:	13.1	93.8	67.6	3.3	35.2	12.0
Moderate, Stable	Count:	13	65	24	7	46	11
	Expected:	9.7	69.2	49.9	2.4	26.0	8.8
	Total:	56	400	288	14	150	51

Table 14. ISOC means and across-class differences in ISOC means between self-perceived academic success classes at Grade 2.

Grade 2	**ISOC M**	**ISOC SE**
Class 1	4.399	0.385
Class 2	3.586	0.090
Class 3	4.310	0.099
Class 4	3.373	0.354
Class 5	3.273	0.140
Class 6	3.050	0.292

	χ^2 Value	**P-Value**
Overall test	60.341*	0.000
Class 1 vs. 2	4.284	0.038
Class 1 vs. 3	0.046	0.830
Class 1 vs. 4	3.830	0.050
Class 1 vs. 5	6.575	0.010
Class 1 vs. 6	7.105	0.008
Class 2 vs. 3	22.665*	0.000
Class 2 vs. 4	0.341	0.559
Class 2 vs. 5	2.897	0.089
Class 2 vs. 6	2.698	0.100
Class 3 vs. 4	6.502	0.011
Class 3 vs. 5	40.299*	0.000
Class 3 vs. 6	16.165*	0.000
Class 4 vs. 5	0.065	0.798
Class 4 vs. 6	0.492	0.483
Class 5 vs. 6	0.471	0.493

Note: ISOC M = the mean level of ISOC for each class in Grade 2.

* Indicates significance at the Bonferroni-corrected level of $p < .0067$.

Table 15. ISOC means and across-class differences in ISOC means between self-perceived academic success classes at Grade 3.

Grade 3	**ISOC M**	**ISOC SE**
Class 1	3.353	0.208
Class 2	3.770	0.054
Class 3	4.163	0.062
Class 4	2.956	0.355
Class 5	3.576	0.094
Class 6	3.472	0.148

	χ^2 Value	**P-Value**
Overall test	57.815*	0.000
Class 1 vs. 2	3.694	0.055
Class 1 vs. 3	12.797*	0.000
Class 1 vs. 4	0.923	0.337
Class 1 vs. 5	0.832	0.362
Class 1 vs. 6	0.206	0.650
Class 2 vs. 3	18.271*	0.000
Class 2 vs. 4	5.135	0.023
Class 2 vs. 5	2.832	0.092
Class 2 vs. 6	3.342	0.068
Class 3 vs. 4	11.203*	0.001
Class 3 vs. 5	28.595*	0.000
Class 3 vs. 6	17.821*	0.000
Class 4 vs. 5	2.664	0.103
Class 4 vs. 6	1.781	0.182
Class 5 vs. 6	0.339	0.560

Note: ISOC M = the mean level of ISOC for each class in Grade 3.

* Indicates significance at the Bonferroni-corrected level of $p < .0067$.

Table 16. ISOC means and across-class differences in ISOC means between self-perceived academic success classes at Grade 4.

Grade 4	**ISOC M**	**ISOC SE**
Class 1	3.062	0.180
Class 2	3.806	0.049
Class 3	4.195	0.046
Class 4	2.300	0.268
Class 5	3.797	0.128
Class 6	3.385	0.087

	χ^2 Value	**P-Value**
Overall test	166.495*	0.000
Class 1 vs. 2	16.164*	0.000
Class 1 vs. 3	37.056*	0.000
Class 1 vs. 4	4.682	0.030
Class 1 vs. 5	7.794*	0.005
Class 1 vs. 6	2.650	0.104
Class 2 vs. 3	28.842*	0.000
Class 2 vs. 4	30.864*	0.000
Class 2 vs. 5	0.004	0.951
Class 2 vs. 6	16.335*	0.000
Class 3 vs. 4	48.177*	0.000
Class 3 vs. 5	8.672*	0.003
Class 3 vs. 6	67.025*	0.000
Class 4 vs. 5	23.386*	0.000
Class 4 vs. 6	15.075*	0.000
Class 5 vs. 6	6.478	0.011

Note: ISOC M = the mean level of ISOC for each class in Grade 4.

* Indicates significance at the Bonferroni-corrected level of $p < .0067$.

Table 17. ISOC means and across-class differences in ISOC means between self-perceived academic success classes at Grade 5.

Grade 5	**ISOC M**	**ISOC SE**
Class 1	3.456	0.172
Class 2	3.740	0.054
Class 3	4.445	0.053
Class 4	2.537	0.336
Class 5	3.448	0.110
Class 6	4.049	0.113

	χ^2 Value	**P-Value**
Overall test	159.899*	0.000
Class 1 vs. 2	2.298	0.130
Class 1 vs. 3	29.775*	0.000
Class 1 vs. 4	5.831	0.016
Class 1 vs. 5	0.001	0.972
Class 1 vs. 6	8.217*	0.004
Class 2 vs. 3	77.625*	0.000
Class 2 vs. 4	12.508*	0.000
Class 2 vs. 5	5.120	0.024
Class 2 vs. 6	5.784	0.016
Class 3 vs. 4	31.386*	0.000
Class 3 vs. 5	67.042*	0.000
Class 3 vs. 6	9.543*	0.002
Class 4 vs. 5	6.442	0.011
Class 4 vs. 6	18.256*	0.000
Class 5 vs. 6	13.974*	0.000

Note: ISOC M = the mean level of ISOC for each class in Grade 5.

* Indicates significance at the Bonferroni-corrected level of $p < .0067$.

Table 18. Cross-tabulation of OSOC trajectory class membership and self-perceived academic success class membership.

OSOC Class	Academic Success Class	High, Decreasing	Moderate/High, Stable	High, Stable	Moderate, Decreasing	Moderate, Stable	Low, Increasing to High
Low/Moderate, Stable	Count:	9	67	23	5	23	7
	Expected:	7.8	55.9	40.2	2.0	21.0	7.1
High, Stable	Count:	19	139	164	3	53	22
	Expected:	23.4	166.8	120.1	5.8	62.6	21.3
Moderate/High, Stable	Count:	10	87	35	1	22	6
	Expected:	9.4	67.2	48.4	2.4	25.2	8.6
High, Low, Moderate/High	Count:	3	6	12	1	8	1
	Expected:	1.8	12.9	9.3	0.5	4.8	1.6
Low, Moderate, Low	Count:	15	101	54	4	44	15
	Expected:	13.6	97.2	70.0	3.4	36.4	12.4
	Total:	56	400	288	14	150	51

Table 19. OSOC means and across-class differences in OSOC means between self-perceived academic success classes at Grade 2.

Grade 2	OSOC M	ISOC SE
Class 1	3.688	0.709
Class 2	3.985	0.305
Class 3	3.961	0.187
Class 4	3.771	0.265
Class 5	3.680	0.289
Class 6	3.115	0.433

	χ^2 Value	P-Value
Overall test	4.738	0.449
Class 1 vs. 2	0.142	0.706
Class 1 vs. 3	0.128	0.720
Class 1 vs. 4	0.012	0.912
Class 1 vs. 5	0.000	0.992
Class 1 vs. 6	0.479	0.489
Class 2 vs. 3	0.003	0.957
Class 2 vs. 4	0.284	0.594
Class 2 vs. 5	0.330	0.566
Class 2 vs. 6	1.798	0.180
Class 3 vs. 4	0.335	0.563
Class 3 vs. 5	1.151	0.283
Class 3 vs. 6	3.982	0.046
Class 4 vs. 5	0.052	0.820
Class 4 vs. 6	1.662	0.197
Class 5 vs. 6	1.504	0.220

Note: OSOC M = the mean level of OSOC for each class in Grade 2.

* Indicates significance at the Bonferroni-corrected level of $p < .0067$.

Table 20. OSOC means and across-class differences in OSOC means between self-perceived academic success classes at Grade 3.

Grade 3	**OSOC M**	**ISOC SE**
Class 1	2.924	0.436
Class 2	3.696	0.114
Class 3	4.369	0.168
Class 4	2.826	0.435
Class 5	3.953	0.267
Class 6	3.591	0.224

	χ^2 Value	**P-Value**
Overall test	20.834*	0.001
Class 1 vs. 2	3.181	0.074
Class 1 vs. 3	7.837*	0.005
Class 1 vs. 4	0.030	0.861
Class 1 vs. 5	2.488	0.115
Class 1 vs. 6	1.958	0.162
Class 2 vs. 3	6.795	0.009
Class 2 vs. 4	3.907	0.048
Class 2 vs. 5	0.638	0.424
Class 2 vs. 6	0.167	0.683
Class 3 vs. 4	10.527*	0.001
Class 3 vs. 5	2.291	0.130
Class 3 vs. 6	6.946	0.008
Class 4 vs. 5	3.902	0.048
Class 4 vs. 6	2.499	0.114
Class 5 vs. 6	0.940	0.332

Note: OSOC M = the mean level of OSOC for each class in Grade 3.

* Indicates significance at the Bonferroni-corrected level of $p < .0067$.

Table 21. OSOC means and across-class differences in OSOC means between self-perceived academic success classes at Grade 4.

Grade 4	**OSOC M**	**ISOC SE**
Class 1	3.290	0.286
Class 2	3.792	0.088
Class 3	4.042	0.121
Class 4	3.355	0.510
Class 5	3.669	0.141
Class 6	4.204	0.151

	χ^2 Value	**P-Value**
Overall test	16.586*	0.005
Class 1 vs. 2	3.151	0.076
Class 1 vs. 3	4.204	0.040
Class 1 vs. 4	0.013	0.911
Class 1 vs. 5	1.064	0.302
Class 1 vs. 6	8.111*	0.004
Class 2 vs. 3	1.854	0.173
Class 2 vs. 4	0.719	0.396
Class 2 vs. 5	0.421	0.516
Class 2 vs. 6	5.213	0.022
Class 3 vs. 4	1.704	0.192
Class 3 vs. 5	5.719	0.017
Class 3 vs. 6	0.676	0.411
Class 4 vs. 5	0.327	0.567
Class 4 vs. 6	2.547	0.111
Class 5 vs. 6	6.343	0.012

Note: OSOC M = the mean level of OSOC for each class in Grade 4.

* Indicates significance at the Bonferroni-corrected level of $p < .0067$.

Table 22. OSOC means and across-class differences in OSOC means between self-perceived academic success classes at Grade 5.

Grade 5	**OSOC M**	**ISOC SE**
Class 1	3.823	0.260
Class 2	3.691	0.105
Class 3	4.182	0.164
Class 4	2.976	0.270
Class 5	3.588	0.161
Class 6	4.153	0.465

	χ^2 Value	**P-Value**
Overall test	19.296*	0.002
Class 1 vs. 2	0.247	0.619
Class 1 vs. 3	1.065	0.302
Class 1 vs. 4	5.000	0.025
Class 1 vs. 5	0.474	0.491
Class 1 vs. 6	0.367	0.545
Class 2 vs. 3	4.175	0.041
Class 2 vs. 4	6.116	0.013
Class 2 vs. 5	0.249	0.618
Class 2 vs. 6	0.863	0.353
Class 3 vs. 4	14.875*	0.000
Class 3 vs. 5	8.416*	0.004
Class 3 vs. 6	0.003	0.955
Class 4 vs. 5	3.743	0.053
Class 4 vs. 6	4.512	0.034
Class 5 vs. 6	1.159	0.282

Note: OSOC M = the mean level of OSOC for each class in Grade 5.

* Indicates significance at the Bonferroni-corrected level of $p < .0067$.

Table 23. Self-perceived academic success: Tests of categorical latent variable multinomial logistic regressions using the 3-step procedure, with 0 = non-Scout, and 1 = Scout.

Likelihood Ratio by Scout=Yes	Estimate	Odds Ratio	Two-Tailed P-Value
Parameterization Using "Moderate/High" Reference Class			
High, Decreasing	0.691	2.00	0.101
Moderate/High, Stable	0.981	2.67	0.023*
High, Stable	0.305	1.36	0.694
Moderate, Decreasing	0.576	1.78	0.244
Low/Moderate, Stable	0.598	1.82	0.289
Parameterization Using "High, Stable" Reference Class			
High, Decreasing	-0.691	-2.00	0.101
High, Stable	0.291	1.34	0.250
Moderate, Decreasing	-0.385	-1.47	0.576
Low/Moderate, Stable	-0.115	-1.12	0.705
Low, Increasing	-0.093	-1.10	0.837
Parameterization Using "Moderate, Decreasing" Reference Class			
High, Decreasing	-0.981	-2.67	0.023*
Moderate/High, Stable	-0.291	-1.34	0.250
Moderate, Decreasing	-0.676	-1.97	0.331
Low/Moderate, Stable	-0.405	-1.50	0.170
Low, Increasing	-0.383	-1.47	0.392
Parameterization Using "Low/Moderate, Stable" Reference Class			
High, Decreasing	-0.305	-1.36	0.694
Moderate/High, Stable	0.385	1.47	0.576
High, Stable	0.676	1.97	0.331
Low/Moderate, Stable	0.271	1.31	0.712
Low, Increasing	0.293	1.34	0.710
Parameterization Using "Moderate, Decreasing" Reference Class			
High, Decreasing	-0.576	-1.78	0.244
Moderate/High, Stable	0.115	1.12	0.705
High, Stable	0.405	1.50	0.170
Moderate, Decreasing	0.271	1.31	0.712
Low, Increasing	0.022	1.02	0.964
Parameterization Using "Low, Increasing" Reference Class			
High, Decreasing	-0.598	-1.82	0.289
Moderate/High, Stable	0.093	1.10	0.837
High, Stable	0.383	1.47	0.392
Moderate, Decreasing	-0.293	-1.34	0.710
Low/Moderate, Stable	-0.022	-1.02	0.964

Note: * indicates a significant odds-ratio.

Table 24. Individually-oriented SOC: Tests of categorical latent variable multinomial logistic regressions using the 3-step procedure, with 0 = non-Scout, and 1 = Scout.

Likelihood Ratio by Scout=Yes	Estimate	Odds Ratio	Two-Tailed P-Value
Parameterization Using "Low, Moderate, Low" Reference Class			
High, Stable	-1.177	-3.22	0.033*
Moderate, Stable	-0.194	-1.21	0.517
Parameterization Using "High, Stable" Reference Class			
Low, Moderate, Low	1.177	3.22	0.033*
Moderate, Stable	0.983	2.67	0.045*
Parameterization Using "Moderate, Stable" Reference Class			
Low, Moderate, Low	0.194	1.21	0.517
High, Stable	-0.983	-2.67	0.045*

Note: * indicates a significant odds-ratio.

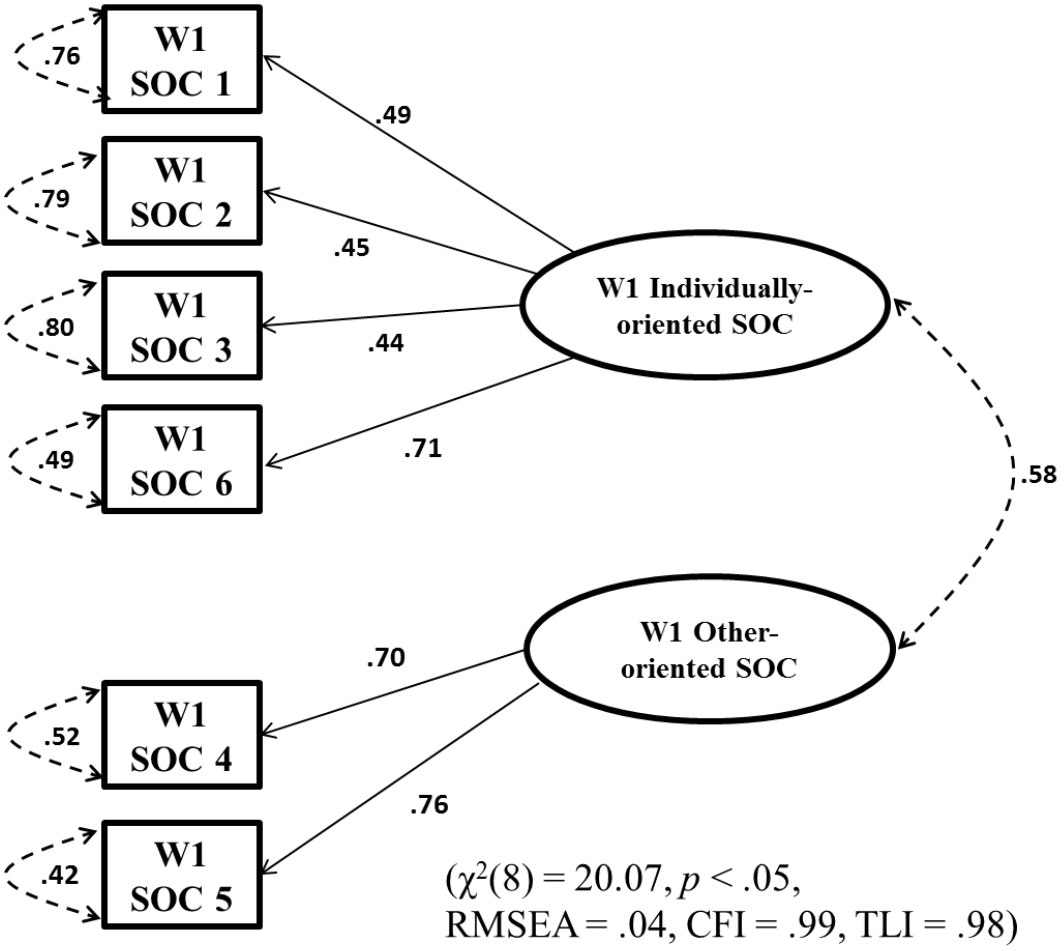

Figure 1. Confirmatory factor analysis of the two-factor model of individually-oriented and other-oriented SOC at Wave 1of the CAMP study (from Chase, 2014). "W1" = Wave 1.

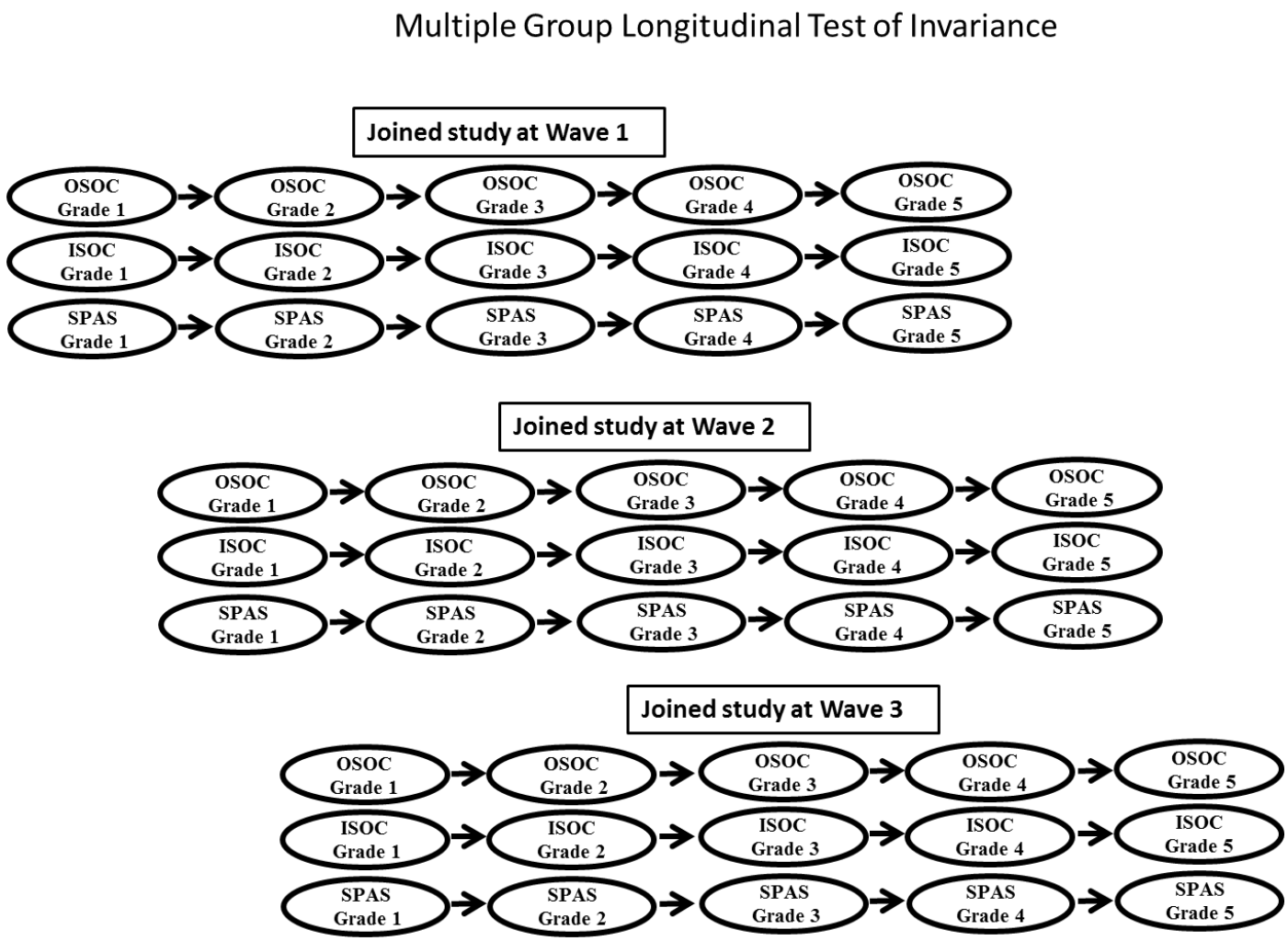

Figure 2. Models of CAMP Study Data for Longitudinal Dissertation Analyses to Test Within-Grade, Across Wave Measurement Invariance, and Across-Grade Measurement Invariance.

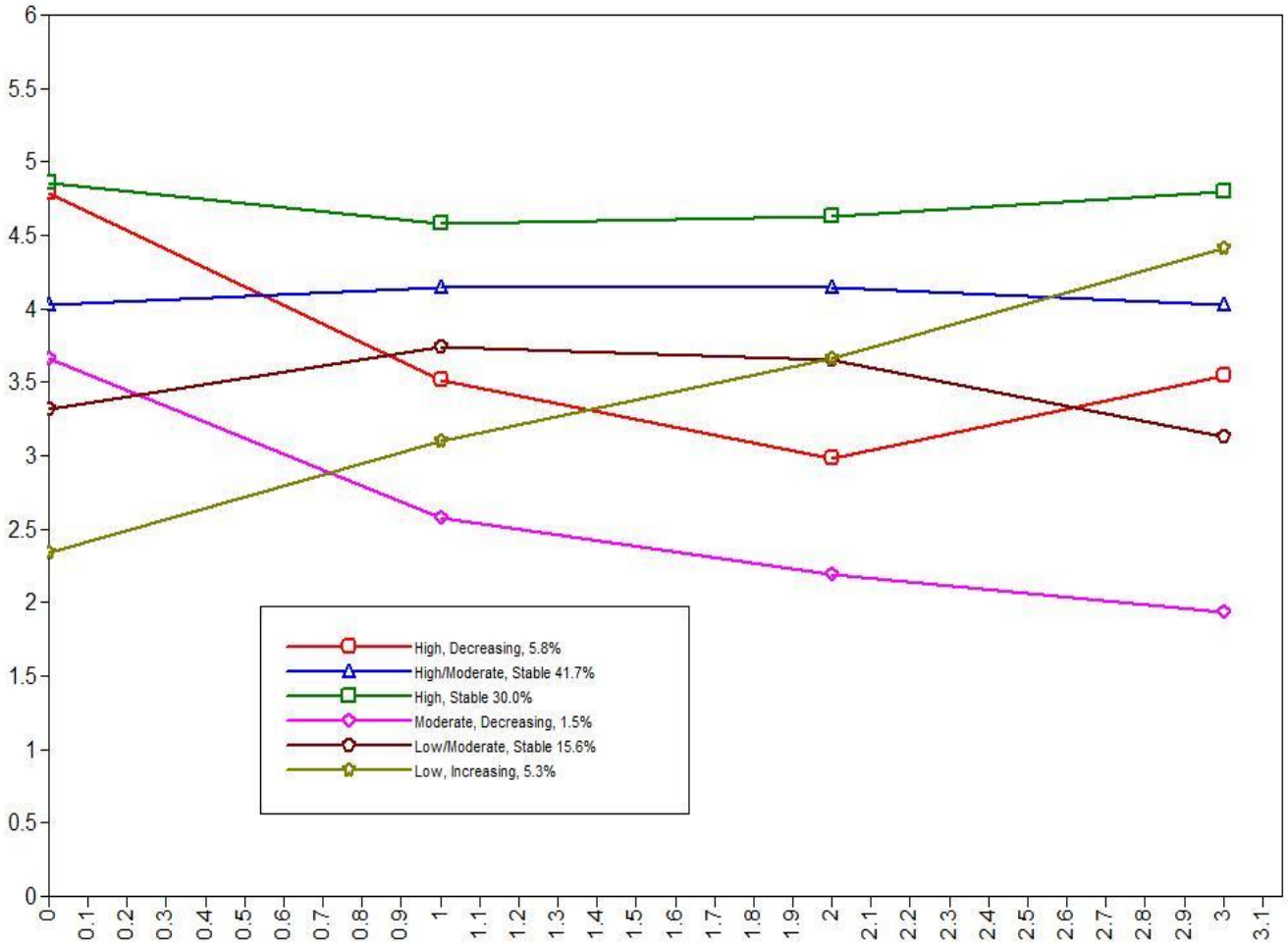

Figure 3. Six-trajectory Class Model of Self-Perceived Academic Success across Grades 2 through 5.

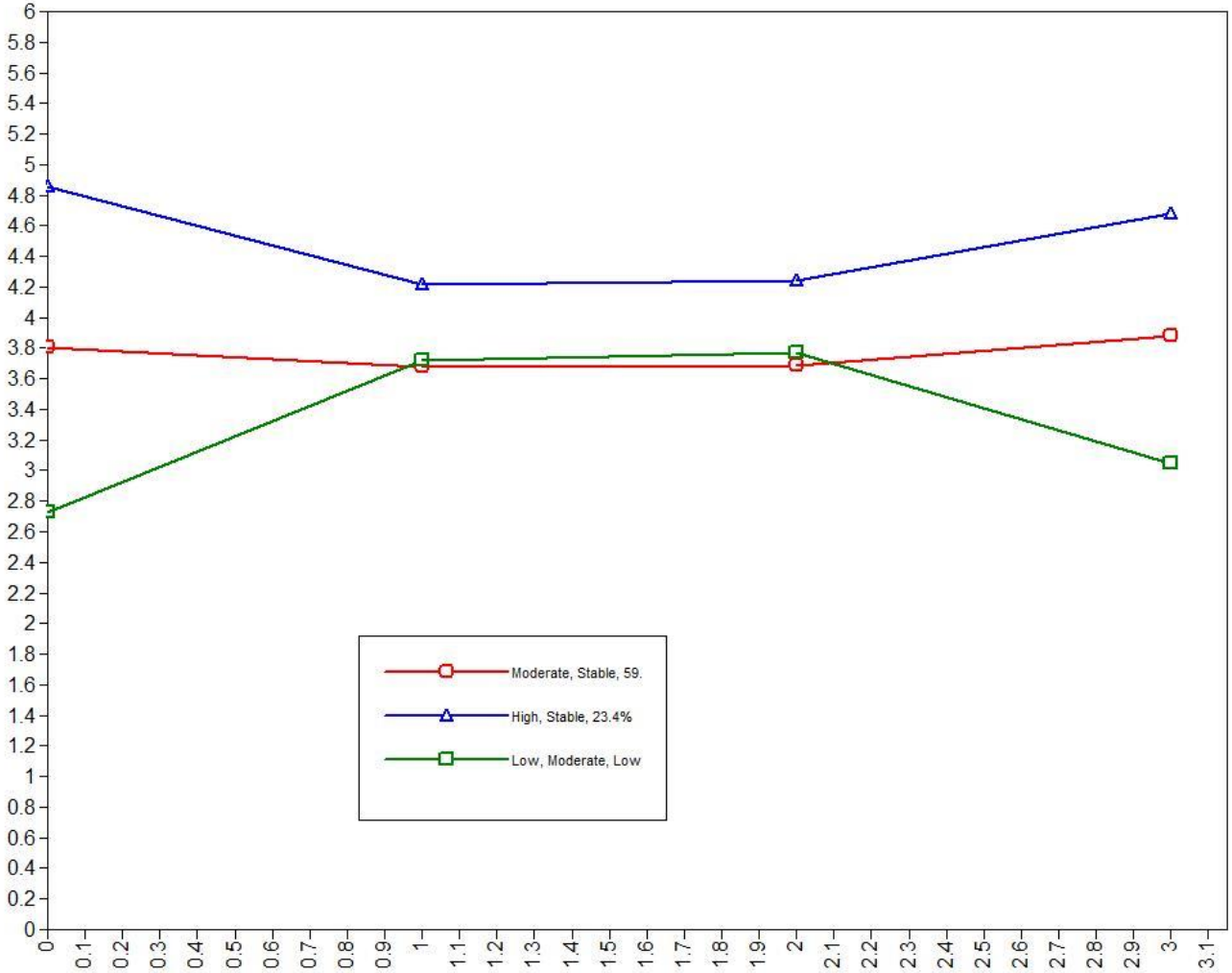

Figure 4. Three-trajectory Class Model of Individually-Oriented SOC across Grades 2 through 5.

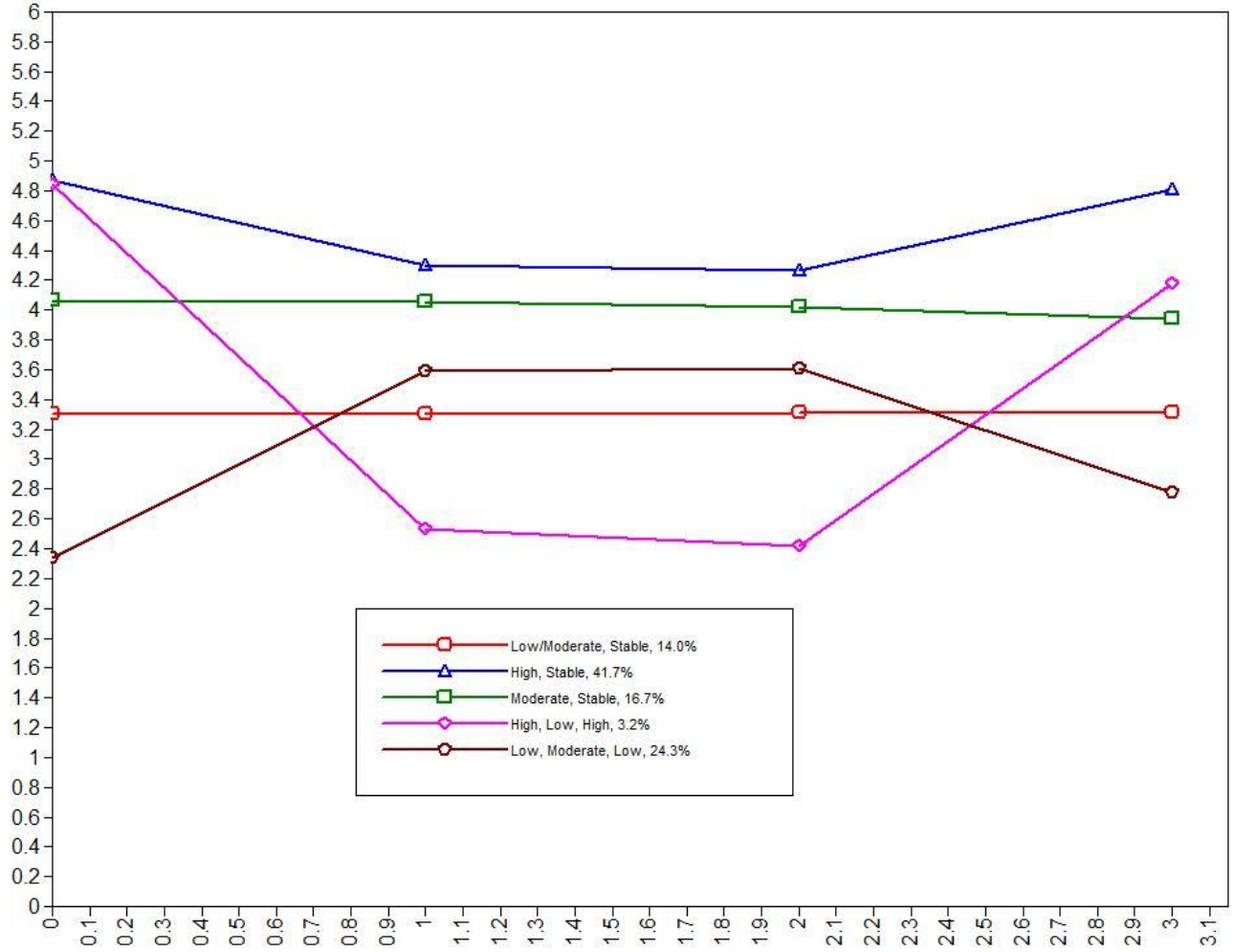

Figure 5. Five-trajectory Class Model of Other-Oriented SOC across Grades 2 through 5.