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More Than the Looking Glass: The Associations Between School-Based Recognitions and Student Self-Concept

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More Than the Looking Glass: The Associations Between School-Based Recognitions and Student Self-Concept

A Thesis submitted in partial satisfaction of the requirements for the degree of

Master of Arts

in

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by

Benjamin Laurence Cornell

September 2017

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ABSTRACT OF THE THESIS

More Than the Looking Glass: The Associations Between School-Based Recognitions and Student Self-Concept

by

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Master of Arts, Graduate Program in Education
University of California, Riverside, September 2017
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Self-concept is related to student academic achievement and locus of control (Coleman et al., 1966), intrapersonal and interpersonal processes (Markus & Wurf, 1987), and many long-term outcomes, such as satisfaction with one’s job, marriage, and life in general (Mortimer et al., 1982). Although self-concept is fairly malleable in early adolescence, it becomes more stable and rigid in high school (Bachman, O’Malley, & Johnston, 1978; Protinsky & Farrier, 1980). While interventions targeting self-concept have generally been found to be successful (Hattie, 2014), the associations between specific school-based recognitions for achievement and student self-concept have yet to be investigated.

Using data from the National Educational Longitudinal Study of 1988 (NCES, 1996), the following analysis investigated the associations between different school-based recognitions for achievement and students’ self-concept. In this study, a set of school-based recognition variables was identified and hierarchical linear modeling (HLM) analyses was used to build an ANCOVA with random effects model predicting student self-concept in the 10th grade while controlling for gender, race, socioeconomic status (SES), and prior self-concept (8th grade) scores. Results indicate support for the use of HLM statistical methods and the inclusion of the aforementioned covariates. However,
none of the predictor variables from the identified set of school-based recognition variables were significantly related to self-concept when entered into the model.

Implications for school psychology research and practice are presented within a multitiered systems of supports (MTSS) framework, including suggestions for the implementation of positive behavioral interventions and supports (PBIS).
Table of Contents

Introduction ......................................................................................................................... 1

Understanding Self-Concept .............................................................................................. 2

Assessing Self-Concept ....................................................................................................... 7

Interventions for Self-Concept ........................................................................................... 8

Self-Concept in High School ............................................................................................... 12

Student Level Variables Associated with Self-Concept ....................................................... 13

Research Questions ........................................................................................................... 14

Methods ............................................................................................................................. 15

Data ..................................................................................................................................... 15

Analyses ............................................................................................................................. 19

Results ............................................................................................................................... 23

Data Cleaning ..................................................................................................................... 23

Research Questions ........................................................................................................... 26

Discussion .......................................................................................................................... 28

Limitations .......................................................................................................................... 29

Summary ............................................................................................................................ 31

References .......................................................................................................................... 32

Tables ................................................................................................................................. 36

Figures ............................................................................................................................... 40

Calculations ........................................................................................................................ 42
More Than the Looking Glass: The Associations Between School-Based Recognitions and Student Self-Concept

Self-concept can be thought of as “a person’s perception of himself” (Shavelson et al, 1976, p. 411). Interest in the construct of self-concept has such deep and varied roots that empirical researchers find themselves citing influential early psychological works, such as W. James (1890) and C.H. Cooley (1902; as cited in Yin & Fan, 2003). Even classical philosophers (e.g., Socrates, Plato, and Aristotle) are referenced in the literature alongside more modern philosophical works such as Nietzsche (trans. 1911; as cited in Hattie, 2014), in order to describe and illuminate the importance of self-concept as a key variable in understanding the human experience.

In a school psychological and educational context, prior studies with student samples have found significant positive relationships between student self-concept and grade point average (Brookover, Thomas, & Paterson, 1964). Similar results have also been identified between academic self-concept and academic achievement (Marsh & Seaton, 2013). Given this correlational evidence, it may be important to identify variables that help to promote student self-concept in the school setting. Therefore, this study investigated which common school-level interventions are associated with their students’ self-concepts. Specifically, this study investigated predictor variables related to school-based recognitions for student participation and achievement in academic areas. As the research literature suggests, it may take more than “the looking-glass” to “know thyself”.
Understanding Self-Concept

Self-concept is a complex construct that goes by many names. Terms interchangeable with self-concept include “self, self-estimation, self-identity, self-image, self-perception, self-consciousness, self-imaginary, and self-awareness” (Hattie, 2014, p. viii). The first writer to use the term, Raimy (1948), defined self-concept as “the map which each person consults in order to understand himself, especially during moments of crisis or choice” (p. 154). A modern definition of self-concept that has become popular amongst researchers comes from the 1976 validity study conducted by Shavelson, Hubner, and Stanton (as cited in Yin & Fan, 2003). Here, the authors broadly and simply define self-concept as “a person’s perception of himself” (Shavelson et al., 1976, p. 411). This definition coincides well with Hattie’s (2014) arguments against the perceived need for a strict operational definition of “self-concept”, similar to other such abstract constructs, such as “intelligence” or “creativity”. From this perspective, a school psychologist trying to define “self-concept” would be analogous to a physicist attempting to define “electricity” or “magnetism”. According to Hattie (2014), both the school psychologist and physicist are researching important concepts, but it would be “absurd and meaningless” (p. 4) to spend time and energy attempting to operationally define these complex concepts. Although a strict operational definition of self-concept may be difficult to formulate, having a widely accepted definition does help to promote understanding across authors, and consumers, of the research literature. Despite the acceptance and popularity of the Shavelson and colleagues (1976) definition (Yin & Fan, 2003), it was not until 1985 that the Oxford English Dictionary (OED) included an
official entry for “self-concept” as a term (Hattie, 2014). The current OED definition for “self-concept” is “a person’s concept or idea of himself” (Oxford English Dictionary, 2017), very closely matching the definition from Shavelson et al. (1976) as noted above.

The psychometric works investigating self-concept, such as those reported by Shavelson and colleagues (Shavelson et al., 1976; Shavelson & Stuart, 1981; Shavelson & Bolus, 1982; Shavelson & Marsh, 1986), provide evidence for the notion that self-concept is a hierarchical, multifaceted construct including both academic and non-academic self-concepts (as cited in Hattie, 2014). A potential representation of this hierarchical model is presented in Figure 1. Here, self-concept is represented as a construct that includes both descriptive components of self-concept, such as considerations of physical appearance, as well as subjective components that exist on a spectrum from lower to higher self-concepts (e.g. perceived academic ability). This theory was refined in 1984 by researchers Song and Hattie, who suggest dividing “academic self-concept” into achievement, ability, and classroom specific self-concepts. Additionally, Song and Hattie (1984) suggested dividing “non-academic self-concept” into social self-concept and presentation self-concept. However, many studies continue to address and label self-concept generally, including components of both academic and non-academic self-concept. Typically, self-concept is measured on a spectrum from lower to higher scores, such that high scores reflect a more positive self-concept.

Although this study is interested in self-concept within a school setting with student populations, it did not focus solely on the academic self-concept component. The chosen dependent variable most closely reflected a global or general self-concept. This is
because of the meaningful outcomes, both near and distal, associated with general self-concept.

**Variables and Outcomes Correlated with Self-Concept.** Self-concept has appeared as a variable of interest in many influential studies. For example, the Coleman Report (Coleman et al., 1966) that famously brought to light the achievement gap between different student populations in the United States found that student self-concept was highly correlated with locus of control. Specifically, research shows that high self-concept is associated with internally, rather than externally, oriented loci of control (Coleman et al., 1996; Fish & Karabenick, 1971). Rotter (1954) describes the locus of control as an individual’s tendency to attribute life experiences to their own actions (internal locus of control) or to factors outside of their control (external locus of control). As shown in the Coleman Report (1966), high self-concept and an internal locus of control were associated with greater student achievement. Interestingly, for white and Asian students, self-concept was more highly associated with academic achievement than locus of control, but for other minority students locus of control was the more highly correlated variable (Coleman et al., 1966). Specifically, Coleman and colleagues (1966) found that minority students, besides Asian American students, generally had a more external locus of control than majority students. However, when minority students do report a higher internal locus of control, their academic achievement is often higher than that of majority students with an external locus of control (Coleman et al., 1966).

In a meta-analysis investigating the correlations between self-concept and measures of achievement, Hattie (2014) found a wide range of results across a total of
128 studies with 1136 correlations. Specifically, the correlations ranged from -0.77 to 0.96 ($M = .21, SE = .007$), with a vast majority of correlations being positive in direction ($n = 944$), compared to 170 negative correlations and 22 correlations of zero (Hattie, 2014). Although this average correlation, $r = .21$, may be seen as small in magnitude, Hattie (2014) argues that this figure must be interpreted relative to other factors. In a 1987 synthesis of meta-analyses, Hattie found that the average correlation of investigated variables purported to improve learning was .22. This research suggests that self-concept is just as highly correlated with achievement as to other key variables such as school aims and policy ($r = .24$), individualization as a method of instruction ($r = .14$), learning hierarchies ($r = .19$), and reinforcement as a learning strategy ($r = .37$). As such, according to Hattie (2014), “compared to other variables, self-concept is a potent correlate of achievement and, given that it is a personological variable, must be regarded as very important” (p. 214). However, the small degree of explained variance found between self-concept and achievement, between 2% to 4%, would suggest that it is very difficult to investigate causal relationships between these constructs (Hattie, 2014).

According to Mill (1869), covariation is the primary criterion for inferring a causal relationship. Similarly, because of the correlational approach used in the meta-analytic research, these findings are unable to support any causal descriptions or causal explanations between self-concept and academic achievement (Shadish, Cook, & Campbell, 2002). Shadish, Cook, and Campbell (2002) describe causal descriptions as the inferred consequences attributable to differences in treatment conditions. Conversely,
causal explanations can be conceptualized as the mechanisms and conditions that allow
the causal relationship to exist (Shadish, Cook, & Campbell, 2002).

Besides academics, self-concept has been found to be associated with other
meaningful life outcomes. One way to conceptualize these outcomes is to organize the
effects mediated by self-concept along intrapersonal and interpersonal processes (Markus
& Wurf, 1987). Intrapersonal processes mediated by self-concept include information
processing, affect regulation, and motivation, while examples of interpersonal processes
mediated by the self-concept include social perceptions, situations and partner choice,
interaction strategies, and reactions to feedback (Markus & Wurf, 1987). Therefore,
general self-concept may mediate academic outcomes, such as motivation in school and
response to teacher feedback, as well as other life outcomes, such as emotional reactivity
in forming and maintaining relationships.

In a longitudinal study investigating the stability of self-concept over a 10 year
span, Mortimer et al. (1982) found that university students with a highly stable self
concept had better relationships with their fathers; greater job security, income,
autonomy, and both extrinsic and intrinsic satisfaction at their place of employment;
greater marital satisfaction; and more life satisfaction in general compared to those with
less stable self-concept scores. Hattie (2014) argues that the relationship between these
factors are reciprocally, and positively, related such that “high stability in self-concept
leads to more satisfaction, which leads to the maintenance of higher self concepts; more
satisfaction can lead to higher self-concepts which leads to more satisfaction” (p. 137).
This coincides well with the findings of Fitts (1981) that suggested that individuals with
higher self-concept experienced a more stable self-concept, compared to others with lower self-concept. Together, these findings suggest that general self-concept, including measures of non-academic self-concept, is a relevant variable in understanding our cognitions, behaviors, affect, and even mental health in the school setting and later in life.

**Assessing Self-Concept**

Similar to the vast and varied interest in the construct of self-concept and the diversity in its conceptualization, there are many different means and approaches to measuring self-concept. For example, Hattie’s (2014) meta-analysis on the associations between self-concept and achievement identified 62 unique tests of self-concept across 128 different studies. In another meta-analysis from the same 2014 text, Hattie identified 93 different measures of change in self-concept across 91 studies.

Despite the variety of measures, Hattie (2014) identifies two tests of self-concept that have become particularly popular in research: the Piers-Harris (Piers & Harris, 1964) and the Coopersmith (1959) tests of self-concept. The Piers-Harris is an 80 item self-report measure for children comprised of dichotomous, “yes” or “no”, responses. As a consequence of its popular use, there is much psychometric data available on this assessment. This data supports the use of the Piers-Harris as a reliable and valid measure of self-concept with school children 8 to 18 years old (Hattie, 2014). Factor analysis of this measure indicates second-order factors relating to academic and non-academic self-concept (Hattie, 2014), matching the theoretical framework proposed by work of Shavelson et al. (1976). Conversely, despite its popularity, the Coopersmith test lacks
convincing evidence for its validity; however, there is research to support its reliability (Hattie, 2014).

**Interventions for Self-Concept**

Interventions aiming to promote self-concept are similarly abundant and diverse. Hattie (2014) categorizes self-concept interventions along a continuum of psychological perspectives and frameworks. For example, Hattie (2014) notes cognitive, behavioral, affective, and existential approaches to improving a client’s self-concept. In his 2014 meta-analysis on changes in self-concept, Hattie (2014) investigated the impact of these different approaches, concluding that these interventions were successful in enhancing self-concept. Furthermore, cognitive based approaches were found to be significantly and consistently more effective than affectively oriented interventions (Hattie, 2014).

Interesting, Hattie’s (2014) meta-analysis also showed differences in the effect sizes of self-concept interventions by setting, such that interventions in an educational setting had an average effect size of 0.36, while other settings produced a higher average effect size of 0.50. This corresponds with previous findings, such as Smith, Glass, and Miller’s (1980) meta-analysis that found that public schools and mental health centers produced smaller effects on enhancing self-concept than college facilities, such as psychology laboratories, therapy training centers, or student counseling services.

This idea of changes in self-concept over time in response to interventions, or other changes in the environment, is not new. In addition to the simple and broad definition of self-concept provided by Shavelson et al. (1976), the authors continued to elaborate on their understanding of this construct by stating that this self-perception is a
product of experience, especially as influenced by “environmental reinforcements and significant others” (Shavelson et al., 1976, p. 411). As this qualifying statement suggests, environmental reinforcers are important predictors of self-concept.

**School-Based Recognitions.** In this study, the “environmental reinforcements” of interest are those explicitly provided by the school for students’ participation and achievement in academic areas and events. These school-based recognitions are environmental reinforcers that may come to influence student self-concept. For example, these recognitions may include receiving awards or academic honors, reinforcement for good attendance or grades, and participation in science fairs or technical competitions. These efforts to proactively impact student self-concept would be considered universal interventions. In a multitiered system of supports, these interventions occur at Tier 1 and should meet the needs of approximately 80% of the school’s population (Glover, 2010). In a multitiered system of supports, nonresponders to the core data-based interventions provided universally at Tier 1, ~15% of the school’s population, would then receive additional targeted supports at Tier 2; and if needed, intensive individualized interventions at Tier 3 for those still needing additional support, ~5% of school population (Glover, 2010). When this model is applied for academics, it is often referred to as Response to Intervention (RTI). One particularly useful application of RTI is that it can be used as a data-based system for determining special education eligibility under the category of specific learning disability (SLD) as permitted by the Individuals with Disabilities Education Improvement Act (IDEIA) of 2004 (Erchul & Martens, 2010).
When the MTSS model is applied for students’ behavioral concerns, including externalizing, internalizing, and social skill related issues, the three-tiered model may be referred to as positive behavioral interventions and supports (PBIS). In fact, along with RTI, IDEIA 2004 promotes the use of these positive behavioral supports (Erchul & Martens, 2010). Examples of positive behavioral supports include: clearly operationalized behavioral expectations that are “taught using direct instructional practices”, every student receiving frequent positive reinforcement for meeting the behavioral expectations, and the communal involvement of all stakeholders in the schools (e.g., every teacher, administrator, office staff, etc.) and those outside of the schools (e.g. family members; Horner, Sugai, & Anderson, 2010, p. 4). Therefore, school-based recognitions can be considered a key element of the “positive reinforcement” component of PBIS. Understanding what particular behaviors to explicitly recognize and positively reinforce is of great value in designing and implementing PBIS. The degree to which schools implement PBIS can be measured with tools such as the School-Wide Evaluation Tool (SET) designed by Horner et al. (2004) to measure their interpretation of School-Wide Positive Behavioral Supports (SWPBS). An aim of this study is to identify specific Tier 1 interventions that come to impact students’ self-concepts. Specifically, this study investigated school-based recognition variables related to students’ participation and success in academic areas as examples of components of PBIS implementation. The school-based recognition variables identified for inclusion, from the NELS data set (NCES, 1996), in this study are listed below in Table 1. A goal of this research is to help
educators identify specific actions that they can take to build or improve their implementation of Tier 1 PBIS.

The implementation of “school-based recognitions” may occur at the classroom or school level. Hattie (2014) identified support in the literature to suggest that classroom environments were meaningfully correlated with student self-concept, specifically, such that higher self-concepts were associated with more positive classroom environments (Johnson, Maruyama, Johnson, Nelson, & Skon, 1981; Slavin, 1983). Similarly, most educators are familiar with the notion that classroom environments are varied to the extent that “some schools are dull, depressing, even terrifying places, while others are lively, comfortable, and reassuring” (Jencks, 1972, p. 256). In one example, Neary and Joseph (1994) found that students who are the victims of bullying report lower self-concept and higher depression scores than non-bullied peers. Therefore, due to the associations between school-environments and self-concept, and the logical interpretation of data such that students are inherently nested within different schools, this study proposes that hierarchical linear modeling (HLM) would be the most appropriate means of statistically investigating the relationship of school-based variables on student self-concept. Without HLM, other regression analyses may fail the assumption of independence of observations (Raudenbush, & Bryk, 2002). A failure of this assumption would severely hinder the interpretability and validity of the statistical results, such that the nested structure of the observations would increase the unexplained variance in the model.
Self-Concept in High School

The development of self-concept is important to study across the lifespan. Whether using Gallup’s (1970) rouge test to assess for infants sense of self, a Piagetian (1977) framework to address cognitive development relating to the sense of self, or using Erikson’s (1950) model to address psychosocial development as it relates to a building of an identity, it appears as though it is important to study the self at various influential periods in the lifespan. The teenage years experienced in a high school setting is one such influential period in an individual’s life. It is during this time, that an individual’s self-concept becomes more rigid and stable, following the instability in self-concept experienced in early adolescence (Bachman, O’Malley, & Johnston, 1978; Protinsky & Farrier, 1980). Longitudinally studying a large sample (n = 2,213) of 10th grade students over 8 years, Bachman and colleagues (1978) found that global self-concept was significantly impacted by new factors that are introduced in the high-school years, such as employment, that are not present to affect middle-school and younger students.

Self-concept is also linked to values and beliefs that come to impact behavioral choices made while in high school (Simpkins & Kean, 2005). For example, self-concept would impact students’ course selection while in high school (Simpkins & Kean, 2005), impacting academic achievement, career path, and other distal outcomes. Similarly, using Eccles et al.’s (1983) Expectancy Value Model, one would expect that self-concept would come to impact values on these academic areas, such that students who believe that they are weak in a subject will come to value that subject less and pursue it less often (as cited in Simpkins & Kean, 2005). This can create both vicious cycles of self-fulfilling
prophecies, separate from the processes underlying stereotype threat (Steele & Aronson, 1995), and Matthew Effects where students with positive self-concepts can continue to better themselves academically, while those with lower self-concepts fall further behind. Other influential choices made in the high school years that are impacted by self-concept include the choice to engage in drug and substance use (Bonaguro & Bonaguro, 1987; Lettieri, 1985).

Because high school appears to be the period of development where self-concept becomes stable (Bachman et al., 1978; Protinsky & Farrier, 1980) and influentially impacts student behavior (Simpkins & Kean, 2005), promoting self-concept in high school may be particularly important and valuable in order to develop and secure a positive self-concept.

**Student Level Variables Associated with Self-Concept**

There are several student level variables associated with self-concept. Prior studies have shown associations between individuals’ gender, race, and SES on their self-concept. Across his literature review on the topic, Hattie (2014) found that there were differences in the mean self-concept scores for men and women on some measured dimensions, but in general, the differences were not as pronounced as some would expect. An example of these gender differences would be the finding that females are apparently more likely to attribute negative attributes to themselves while men are more likely to identify with positive attributes (Hattie, 2014). As previously mentioned, the Coleman Report (Coleman et al., 1966) demonstrated meaningful differences in the locus of control and achievement across racial groups as they correlate with self-concept. Even
more so, individuals from different nations may conceptualize and report differently on measures of self-concept (Hattie, 2014). Additionally, according to a meta-analysis conducted by Hattie (2014), lower SES individuals were more likely to respond positively to interventions designed to improve self-concept compared to other SES groups. For these reasons, gender, race, and SES may be included as covariates in models predicting self-concept.

Similarly, studies investigating high school self-concept scores may benefit from controlling for the influence of students’ prior self-concept. For example, self-concept reported during the base year of NELS data collection, 8th grade, would reflect self-concept scores at the end of middle school. As such, these scores may influence their first follow up self-concept scores in the 10th grade. As shown by Protinsky and Farrier (1980), self-concept is still unstable during this period of adolescence. Therefore, the following HLM model will address how specifically high-school experiences, reported in the 10th grade, are associated with student self-concept while controlling for the self-concept that students had reported in middle school. Furthermore, this model also considers gender, race, and SES as covariates in order to better understand the associations between school-based recognition variables and student self-concept in the 10th grade.

**Research Questions**

This study investigated if and to what extent hypothesized school-based recognition variables of interest, listed in Table 1, are significantly associated with student self-concept in the 10th grade. Furthermore, this study aimed to address the
substantive interpretation of the coefficients associated with each significant variable identified by the final HLM model. In other words, what is the direction and magnitude of the influence of the independent variables on students’ 10th grade self-concept? Answers to this question may help school psychologists, especially those in a high school setting, to better understand how particular, Tier 1, school-based recognitions may come to impact students’ self-concept.

Methods

Data

The data used to investigate this research questions were previously collected by the National Center for Education Statistics (NCES), starting in 1988 with a cohort of 8th grade students, as a part of the National Education Longitudinal Study (NELS). The collected data set included survey information from base year through the third follow-up, 1994, two years following high-school graduation. A goal of this particular study was to better understand the influence of high school recognitions that may shape self-concept. As such, the first follow up data provides a great source of data that would reflect early high school experiences, 10th grade. The base year data, from 8th grade, as previously mentioned, was used to control for self-concept reported at the end of middle school. The other follow up data, second and third follow up, would be less appropriate for this research question. The second follow up would not be appropriate because of the limited implications of the findings, as they would apply to a student population who are about to graduate from high school and would not be present to receive many additional interventions linked to school-based recognitions. Similarly, by the third follow up
students have already graduated high school. However, if we learn more about the influences of 10th grade self-concept, then those influences could be actively applied for the remainder of the high school experience. Therefore, research questions and results were interpreted in respect to students in the 10th grade, measured in 1990.

In the 1988 base year, the sampling procedure was a “clustered, stratified national probability sample of 1,052 public and private eight-grade schools with almost 25,000 students across the United States participating” (NCES, 1996). In the first follow-up, from which this study is primarily interested, 21,000 students were sampled in 1990 of their 10th grade year (NCES, 1996). To be included as a participant in this study, a student must have taken the F1 questionnaire regarding school-based recognitions for achievement and similarly have a corresponding F1 School Identification code.

**Variables.** The variables identified for inclusion in analysis were selected because of their relevance to the research question. The outcome variable identified from the NELS data is first follow-up Self-Concept2 (F1CNCPT2). While another variable, first follow up Self-Concept1 (F1CNCPT1), is also included in the NELS data, it was designed to be as comparable with other, older data sets (NCES, 1996). However, Self-Concept2 is a new variable constructed as a composite from other variables in the current NELS data set. As such, Self-Concept2 may be interpreted more readily and without reference to other data sets. Therefore, Self-Concept2 is the preferred variable for inclusion in this study, as this study seeks to be highly generalizable and replicable. For the remainder of this paper, for ease of readability, Self-Concept2 will simply be referred
to as Self-Concept. F1-Self-Concept will refer to the dependent measure taken at first follow up while BY-Self-Concept will refer to scores from the base year data.

F1-Self-Concept is a continuous, mean composite variable, comprised of seven unique variables (NCES, 1996). These variables are: “respondent feels good about him/herself”, “respondent feels s/he is a person of worth”, “respondent able to do things as well as others”, “on the whole, respondent’s satisfied with self”, “respondent feels useless at times”, “at times, respondent thinks he is no good at all”, and “respondent does not have much to be proud of” (NCES, 1996). These seven variables were scored on a four point Likert scale ranging from 1, agree, to 4, disagree. The first four variables were reverse scored such that the magnitude of the composite is interpreted to mean that higher scores represent more desirable responses. Using Song and Hattie’s (1984) interpretation of the multifaceted self-concept, this F1-Self-Concept composite variable most closely aligns with a global self concept with elements of non-academic self-concept, specifically, presentation self-concept’s sub category of “confidence in self” or “emotional self concept”.

Similarly, the covariate of BY-Self-Concept (BYCNCPT2) is a continuous, composite variable comprised of same seven question items as F1CNCPT2, but asked two years prior in the 8th grade (NCES, 1996). Both BY-Self-Concept and F1-Self-Concept are the mean composites of their corresponding seven Likert scale items. Each of the seven items are separately standardized, such that they have a mean of zero and a standard deviation of 1, by using z-scores and corresponding sampling weights.
Therefore, BYCNCPT2 and F1CNCPT2 measure the same construct in the same way, but at two different time points, 1988 and 1990 scores respectively.

The independent variables identified for inclusions were 10 first-follow-up variables relating to school-based recognitions for achievement. Specifically, these variables come from a survey questionnaire in NELS (1996) that posed a single question, “Some students are recognized by their school or community. In the first half of the school year, did you win any of the following awards or were you recognized for doing well or participating in certain activities” (p. 190)? Then, the student is prompted with 10 items to which they can respond with “applies” or “does not apply”. These 10 different response items for this question were selected as variables for inclusion because of the theoretical support that these recognitions for achievement could be associated with self-concept (Hattie, 2014; Marsh & Seaton, 2013). These 10 variables are presented below in Table 1. These variables are all scored on a dichotomous scale where a response of 1 indicates, “applies” while responding 2 indicates, “does not apply” (NCES, 1996).

The other covariates in the model are gender, race, and SES. Gender, composite sex (SEX), is scored such that 1 indicates male and 2 indicates female (NCES, 1996). This data was acquired from base year reports and school records if needed. If this data could not be found, the case would be randomly assigned a value of 1 or 2 (NCES, 1996). Similarly, regarding the covariate of race, composite race (RACE) was constructed using base year reports. If unavailable, parent and school reported data were used to assign race to a case (NCES, 1996). In the NELS data set, the following five racial groups were assigned a number. Students identifying as Asian and/or Pacific Islander were assigned a
Students identifying as Hispanic were assigned a 2. Similarly, students identifying as Black, not Hispanic were assigned a 3, while students reporting as White, not Hispanic were assigned a 4. Students were assigned a 5 when identifying as American Indian and/or Alaskan native (NCES, 1996).

The covariate of SES, base year socio-economic status composite (BYSES), is a continuous variable comprised of several factors. In the NELS data set, SES is constructed using parent questionnaires to incorporate data relating to father’s and mother’s education level, father’s and mother’s occupation, and family income. Similar to the other continuous variables in this data set, BY and F1-Self-Concept, this variable has already been computed using standardized values with a mean of zero and a standard deviation of one. Again, similar to the other continuous variables, higher values represent more desirable responses.

Analyses

Data Cleaning. Data were cleaned and prepared for analysis following the procedures outlined by the NELS data codebook (NCES, 1996). Data was first cleaned by recoding the variables such that missing values, as coded by NCES (1996), would be read correctly as missing by SPSS, one of the statistical software packages used in these analyses. This was done by coding values 8 and 99.98 to become “system missing” in the Self-Concept variables and by coding values of 8 as “system missing” in the independent variables. In RACE, values of 8 were also coded as “system missing”, as were values of “99.998” in the variable of BYSES. In this study, the nominal variables of gender and race were dummy coded such that males and Caucasians are the referenced groups.
Dummy coding procedures occurred after correcting for outliers and missing data. Before further adjusting the data set, descriptive statistics for the yet-to-be cleaned data set were recorded in Tables 2 and 3 to ensure that these findings matched the descriptive statistics as described in the NELS electronic codebook (NCES, 1996).

Data were then cleaned by adjusting for outliers and missing data. First, participant cases that did not participate in the school-based recognition questionnaire or have a corresponding F1-school identification number were removed from analyses. This will allow analyses to directly answer the research question by only including first follow up students who had access to this school-based recognition questionnaire through which the independent variables are constructed. Similar to the methods used by Shapiro and colleagues (2017), data was then screened for outliers prior to correcting for missing data. Outliers were identified in the continuous variables by converting responses to z-scores to identify values outside of +/- 3 standard deviations from the mean. This was carried out in SPSS and then cases with outliers were manually listwise deleted in order to remove the influence of those cases from the analyses to follow. For example, outliers may skew the distribution, altering mean and variance values, and therefore negatively impact the multiple imputation process. Next, missing data was corrected for by multiple imputations. This decision was made after reviewing the nature of the missing data and following the advice presented by Scheffer (2002). Specifically, Scheffer (2002) advocates for the use of multiple imputations and recommends avoiding case deletion or mean imputation unless the data is missing completely at random.
Finally, in order to ensure that results are generalizable to the proposed populations of interest, appropriate weights must be applied when possible. Weights are particular variables applied to a dataset to adjust for the “unequal probabilities of selection” and to compensate for non-response (NCES, 1996). These weights, and instructions for their use, are provided in the NELS electronic codebook (NCE, 1996). Since this model used data from both the base year and first follow up, the F1PNLWT weight was applied throughout the data cleaning process. Once data had been cleaned and completely prepared, descriptive statistics were recorded again on Tables 4 and 5. This allows for a comparison between the original and cleaned data sets.

**Statistical Methods.** Once data had been cleaned and organized with the use of SPSS, the statistical software package HLM 7 was used to build the hierarchical linear model. In this study, the covariates are entered into the model at level one to represent student level variables. The independent variables are entered into level two of the model as means aggregated across schools using the school identification code (SCH_ID) variable associated with each student (ID).

The first step in the model building process was to simply build a One-Way ANOVA model with only F1-Self-Concept included as the dependent variable. The corresponding Chi-Square statistic of this fully unconditional model indicates whether the total variance is significantly greater than zero, indicating whether there is significant variation in the mean student self-concept scores across schools in the 10th grade. This allowed insight into the appropriateness of the HLM methodology. If there is was significant variation, then a traditional ANCOVA methodology would have been adapted.
The next step, after finding support for the HLM model, was to build a student level model to include the influence of the covariates. Likelihood ratio tests (LRT) were conducted at each step of the model building process to see if the new model was significantly different than the last. Next, an exploratory school-level model was ran with all 10 variables in order to answer the first half of the research question. The results from that model indicate which variables are significantly related to F1-Self-Concept and would be entered into the final School-Level model. In the proposed final school level model identified by the HLM analyses, the associated Chi-Square statistic would indicate whether the proportion of total variance explained by the model is significantly greater than zero, indicating additional support or evidence against the statistical techniques when considering all variables and covariates.

Similarly, the same HLM 7 output would help to answer the remainder of the research question by identifying which of the hypothesized independent variables are statistically significant and suggest the magnitude and direction of their influence. Specifically, a table was created (Table 6) to show the parameter estimates and all axillary statistics associated with the HLM model building process. Significant coefficients are marked with an asterisk, or two, to indicate level of statistical significance.

Assumptions of the regression model include the distributional assumptions to be linear as well as independent and identically distributed (iid). These are the assumptions of independence, normality, and homogeneity of variance. Each of these assumptions can be checked at Level 1 and Level 2 of analyses. For example, at Level 1, the assumption
of linearity can be checked by plotting 10th grade self-concept against each continuous predictor variable (i.e., BY-Self-Concept and SES). The assumption of independence could be addressed through rational reasoning and interpretations of the source of data. Here, although students are nested within schools, suggesting a violation of this assumption, the HLM methodology accounts for this structure and allows for meaningful interpretation of results. The assumption of normality can be addressed by graphing the residuals of the model along normal probability plots. Here, deviations from the line representing normality would indicate a violation of the assumption. Similarly, the assumption of homogeneity of variance can be addressed through a scatterplot of the Level 1 residuals and predicted values. In these graphs, a homoscedastic pattern would show support, while heteroscedastic patterns would indicate a violation of the assumption. Assumptions of the model at Level 2 can be checked similarly. For the assumption of normality, the residuals at Level 2 could be plotted on a normal probability plot. Similar to the assumption check at Level 1, data points deviating from the line of normality would suggest a violation of the assumption of normality. The assumption of homogeneity of variance could be checked by plotting Level 2 residuals and Empirical Bayes estimates. Similar to Level 1 assumption checks, a homoscedastic pattern would indicate the assumption is not violated.

Results

Data Cleaning

Descriptive statistics for the original, un-cleaned data set are provided in Tables 2 and 3. This data started with a total of 14,915 students represented in the data across
1,573 different schools. Here, 12,211 10th grade students have taken the questionnaire containing the independent variables, indicating 18.13% missing data (Table 2). As such, the maximum sample size for this study would be $n = 12,211$ if not for the aforementioned planned data cleaning procedures. This corresponds with the values reported in the NELS codebook (NCES, 1996). A review of the continuous variables present in the data set is also useful to preliminarily inspect these variables for a normal distribution. As seen in Table 3, BY-Self-Concept, SES, and F1-Self-Concept all appear to be normally distributed, with skew and kurtosis values less than $\pm 2$ (Field, 2009), and they have means and standard deviations of approximately 0 and 1 respectively. Therefore, the aforementioned data cleaning methods appear to be appropriate. Before creating $z$-scores to identify outliers, all cases in which the student participant did not take the questionnaire with the independent variables ($n = 2704$) were listwise deleted from analyses. Similarly, remaining cases without corresponding F1 School Identification codes were also listwise deleted ($n = 197$), representing an additional 1.61% loss of remaining data. Following these steps, a remaining valid $n = 12,014$ participants remained in the data set for analyses because they met the primary inclusion criteria of having both completed the school-based recognition questionnaire and have a corresponding F1 School ID.

After transforming the continuous variables into $z$-scores, a number of outliers were identified. These cases with outliers, 131 in total, represented 1.09% of the sample. In BY-Self-Concept, 69 outliers were identified as falling outside of 3 standard deviations from the mean and the associated cases were listwise deleted. In SES, only six
outliers were identified and similarly deleted. Finally, a remaining 56 outliers were identified and corresponding cases were listwise deleted from F1-Self-Concept. This process has reduced the sample from \( n = 12,014 \) to \( n = 11,883 \). However, this reduction of 1.09% in sample size will greatly help the following multiple imputation process because the remaining data set will be free of extreme and influential data points. As such, I deleted 1.09% of cases so that the remaining missing data points (i.e., the 4.62% missing in SEX, 5.50% in RACE and BY-SES, 3.90% in F1-Self-Concept, and the 5.13% missing in BY-Self-Concept) could be computed with greater validity. In other words, I removed a few data points to better save many data points. At this point in the data cleaning process, a grand total of 328 student cases have been removed from the original sample of \( n = 12,211 \), representing a 2.68% loss in sample size in order to identify students that meet inclusion criteria and to remove cases with extreme values.

Multiple imputations were then carried out through SPSS, using automatic imputation methods, defaulting to 5 imputations. Logistic regression was the type of imputation model used for the independent variables, race, and gender due to their dichotomous scales, while linear regression was used for the continuous Self-Concept variables and BY-SES. Following this procedure, there were no longer any missing data from the dataset as seen in Tables 4 and 5. Similarly, in Table 5, it appears as though the continuous variables have maintained their approximately normal distributions, means of zero, and standard deviations of 1. In this final prepared data set, there are 11,883 student cases represented across 1,430 different schools.
Research Questions

After having cleaned the data, I ran the HLM model in HLM 7. Results of each stage of the model building process are documented below in Table 6.

Support for HLM Methodology: As previously stated, the Chi-Square statistic of the fully unconditional model can be used to test the appropriateness of the HLM methodology. From these findings, results indicate that the Chi-square statistic of the One-Way ANOVA model indicates that the proportion of total variance is significantly greater than zero, $\chi^2 = 1649.227, p < .001$, indicating that there does appear to be significant variation in the mean student F1-Self-Concept scores across schools in the 10th grade. The corresponding intra-class correlation (ICC) coefficient, $ICC = 0.021$, indicates that 2.1% of the total variance in mean F1-Self-Concept is between schools (Raudenbush & Bryk, 2002). This finding supports the aforementioned HLM model building process as planned. Following this finding, the HLM methodology continued as planned without reverting to an ANCOVA model.

Influence of Covariates: As seen in Table 6, all hypothesized covariates of interest were significant in the model, except for students identifying as Asian or Pacific Islander ($\gamma_{40} = -0.011, p > .05$) when compared to students identifying as White, not Hispanic. This is consistent with other findings, for example, the Coleman Report (1966), which indicated that Asian American students score more similarly to majority students, compared to other minority students on constructs such as self-concept, locus of control, and academic achievement.
When these covariates are entered into the student level model, there is a significant difference in model fit, as indicated by the Likelihood Ratio Test (LRT), $LRT = 3221.268$, $p < .001$. Additionally, the proportion of variance in level 1, $r_{ij} = .228$, indicating that the student level model explains an additional 22.8% of the variance in individual student 10th grade self-concept scores when compared to the fully unconditional model. Similarly, the proportion of variance in level 2, $\mu_{0j} = .778$, indicates that the consideration of these covariates into the model accounts for an additional 77.8% of the total variance in school mean 10th grade self-concept scores when compared to the fully unconditional model. This supports the hypothesis underlying the HLM methodology such that these covariates (i.e., gender, race, SES, and 8th grade Self-Concept) are significantly and influentially linked to student 10th grade self-concept.

However, it would appear as though the addition of these variables into the model had meaningfully reduced the significance of the model fit. The Chi-square statistic of this student level model indicates that the proportion of total variance is no longer significantly greater than zero, $\chi^2 = 1430.472$, $p = .484$, indicating that there does not appear to be significant variation in the mean student self-concept scores across schools in the 10th grade when controlling for gender, race, SES, and 8th grade self-concept. The corresponding conditional ICC, $ICC = 0.006$, indicates that now only 0.6% of the total variance in mean F1-Self-Concept is between schools, since bringing the covariates into the model (Raudenbush & Bryk, 2002).

**Influence of Independent Variables:** After building the student level model, the 10 independent variables were added into the model at level 2 to determine which of
these hypothesized variables were significantly associated with F1-Self-Concept. Results of this exploratory school model are shown below in Table 6. Here, analyses indicate that none of the 10 variables are significantly associated with 10th grade self-concept when controlling for student gender, race, SES, and 8th grade self-concept. Unfortunately, without finding significant independent variables in the exploratory model, a final school level model cannot be built with any of these hypothesized variables of interest included. As such, the model building process stops here.

**Discussion**

From these HLM analyses, interesting results are found. First, it does appear as though there is significant variation in the mean 10th grade self-concept scores for students across schools ($\chi^2 = 1649.227, p < .001$). However, when controlling for their gender, race, SES, and prior self-concept, the model no longer shows that significant variation across school ($\chi^2 = 1430.472, p = .484$). Of the 10 hypothesized independent variables of interest, none were found to be significant for a final school-level model.

For policy, this would suggest that schools do differ in the mean 10th grade self-concept scores of their students. However, student self-concept does not appear to be significantly related to any of the 10 school-based recognition variables from the NELS data set (Table 1). However, differences in student 10th grade self-concept scores are more closely related to their students’ gender, race, SES, and prior self-concept. This would suggest that student level variables in the 8th grade (e.g., minority status, SES, and self-concept) could be used as indicators for risk regarding their 10th grade self-concept. Students at risk for low 10th grade self-concept may benefit from interventions targeting
self-concept. Unfortunately, it does not appear as though the school-based recognition variables investigated in this study are associated with 10th grade self-concept. These findings suggest that it may take more than individual actions like awarding students for attendance (F1S8E) or participating in a science fair (F1S8D) to see associations on 10th grade self-concept. However, identifying correlates of student-self concept, especially at the school level, may be beneficial to understanding student well being, as shown in the wealth of literature linking self-concept to other life outcomes, including academic achievement and job satisfaction (Hattie, 2014). Perhaps more unified efforts, such as fully developed school-wide positive interventions and supports, would be associated with student self-concept even if smaller scale efforts, such as receiving recognition for writing an essay (F1S8F), were not significant when considered by themselves. Future studies could expand upon this research by creating a composite variable across the 10 identified school-based recognition variables. This composite, representing the degree to which each student experienced various school-based recognitions, could then be entered into the school-level model as an independent variable. If significant, that would suggest that the school-based recognition variables identified might actually be meaningfully associated with student self-concept, but only when applied together.

**Limitations**

As previously stated, this study seeks to be highly generalizable. For example, the use of a nationally representative sample in a regression analysis is beneficial for this objective in its production of descriptive results. However, while these efforts have helped to establish the external validity of this methodology, it is to the expense of
internal validity. As such, a limitation of this design is that it does not allow for a high degree of causal inference. In other words, this study is not an empirical experiment. However, efforts to statistically control for known moderating or mediating variables were taken through the inclusion of the covariates gender, race, SES, and prior self-concept. Although this does not allow for causal descriptions or explanations (Shadish, Cook, & Campbell, 2002), the effort to statistically account for known covariates does improve internal validity as well as the generalizability of these findings.

The generalizability of these findings also benefit from the quality of the source of the data. The NELS data set (NCES, 1996), after data cleaning, included a sample of 11,883 students across 1,430 different schools. This large sample, taken nationally as a clustered, stratified national probability sample, helps the findings generalize to other 10th grade students across other high schools in the United States. However, another limitation is the age of the data, having been collected 27 year ago. Yet, despite its age, the quality of the data justifies its use for these purposes.

The self-concept composite variable used as the dependent variable more closely reflects general self-concept, including non-academic self-concept items. Future studies may benefit from studying a dependent variable that is explicitly and exclusively constructed to represent academic self-concept. In the school setting, it is possible that stronger associations exist between school-based recognitions for academic achievement and specifically academic self-concept, as opposed to general self-concept. Unfortunately, the NELS data set did not include such a variable (NCES, 1996).
Summary

Although some limitations exist in this study, they do not devalue the findings. This study demonstrates that the particular school-based recognition variables, when considered individually and when controlling for gender, race, SES, and 8th grade self-concept, are not significantly associated with 10th grade self-concept. The limitations presented simply suggest areas for future research, whether that entails using a more modern data set or including a new composite predictor variable. Similarly, this study does establish significant variation between student self-concept scores across schools, indicating support for HLM methodologies. Finally, this study also suggests the importance of considering gender, race, SES, and prior self-concept scores when modeling student 10th grade self-concept. Future studies may benefit from these findings in designing new research projects. School psychologists and educators may benefit from these findings in their design and implementation of PBIS in a MTSS framework. Specifically, this study shows that individual, discrete school-based recognitions may not be enough to find significant relationships with student self-concept in the 10th grade. It may take more unified, comprehensive approaches to school-based recognitions for achievement before significant relationships are found for student self-concept.
References


Tables

Table 1

*School-Based Recognition Variables Investigated in NELS*

<table>
<thead>
<tr>
<th>Variable</th>
<th>Label</th>
</tr>
</thead>
<tbody>
<tr>
<td>F1S8A</td>
<td>Respondent has not won any awards</td>
</tr>
<tr>
<td>F1S8B</td>
<td>Respondent elected officer of a school class</td>
</tr>
<tr>
<td>F1S8C</td>
<td>Respondent has won an academic honor</td>
</tr>
<tr>
<td>F1S8D</td>
<td>Respondent participated in a science or math fair</td>
</tr>
<tr>
<td>F1S8E</td>
<td>Received recognition for good attendance</td>
</tr>
<tr>
<td>F1S8F</td>
<td>Received recognition for good grades</td>
</tr>
<tr>
<td>F1S8G</td>
<td>Received recognition for writing essay</td>
</tr>
<tr>
<td>F1S8H</td>
<td>Named most valuable player on sport team</td>
</tr>
<tr>
<td>F1S8I</td>
<td>Received a community service award</td>
</tr>
<tr>
<td>F1S8J</td>
<td>Participated in voc/tech competition</td>
</tr>
</tbody>
</table>

Table 2

*Descriptive Statistics for Categorical Variables before Data Cleaning*

<table>
<thead>
<tr>
<th>SEX</th>
<th>RACE1</th>
<th>F1S8A</th>
<th>F1S8B</th>
<th>F1S8C</th>
<th>F1S8D</th>
<th>F1S8E</th>
<th>F1S8F</th>
<th>F1S8G</th>
<th>F1S8H</th>
<th>F1S8I</th>
<th>F1S8J</th>
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<td>12211</td>
<td>12211</td>
<td>12211</td>
<td>12211</td>
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<td>12211</td>
<td>12211</td>
<td>12211</td>
</tr>
<tr>
<td>Female</td>
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<td>.</td>
<td>.</td>
<td>.</td>
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<td>.</td>
<td>.</td>
<td>.</td>
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<td>.</td>
</tr>
<tr>
<td>RACE1</td>
<td>.</td>
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<td>.</td>
<td>.</td>
<td>.</td>
<td>.</td>
<td>.</td>
<td>.</td>
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</tr>
<tr>
<td>RACE2</td>
<td>.</td>
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<td>.</td>
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<td>.</td>
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<tr>
<td>RACE3</td>
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<td>1464</td>
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<td>.</td>
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<td>.</td>
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<tr>
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<td>RACE5</td>
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</tr>
<tr>
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<td>.</td>
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<td>1983</td>
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<td>1772</td>
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<td>1136</td>
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<td>11075</td>
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</table>

*Coding for RACE corresponds with NELS Dataset and Codebook (NCES, 1996), such that RACE1 – RACE5 respectively refer to students identifying as Asian/Pacific Islander, Hispanic, Black not Hispanic, White not Hispanic, or American Indian / Alaska Native.*
Table 3

Descriptive Statistics for Continuous Variables before Data Cleaning

<table>
<thead>
<tr>
<th>BY-Self-Concept</th>
<th>BY-SES</th>
<th>F1-Self-Concept</th>
</tr>
</thead>
<tbody>
<tr>
<td>Valid N</td>
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<td>13820</td>
</tr>
<tr>
<td>% Missing</td>
<td>7.91</td>
<td>7.34</td>
</tr>
<tr>
<td>Mean</td>
<td>0.022</td>
<td>-0.1320</td>
</tr>
<tr>
<td>Std. Deviation</td>
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<td>0.7869</td>
</tr>
<tr>
<td>Minimum</td>
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<td>-2.97</td>
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<tr>
<td>Maximum</td>
<td>1.23</td>
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<td>Skew</td>
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<tr>
<td>Kurtosis</td>
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Table 4

Descriptive Statistics for Categorical Variables after Data Cleaning

<table>
<thead>
<tr>
<th>SEX</th>
<th>RACE1</th>
<th>RACE2</th>
<th>RACE3</th>
<th>RACE4</th>
<th>RACE5</th>
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</thead>
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<td>0</td>
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<td>.</td>
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</tr>
<tr>
<td>RACE2</td>
<td>.</td>
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<td>.</td>
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</tr>
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<td>Applies</td>
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</table>

1Coding for RACE corresponds with NELS Dataset and Codebook (NCES, 1996), such that RACE1 – RACE5 respectively refer to students identifying as Asian/Pacific Islander, Hispanic, Black not Hispanic, White not Hispanic, or American Indian / Alaska Native.

Table 5

Descriptive Statistics for Continuous Variables after Data Cleaning

<table>
<thead>
<tr>
<th>BY-Self-Concept</th>
<th>BY-SES</th>
<th>F1-Self-Concept</th>
</tr>
</thead>
<tbody>
<tr>
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</tr>
<tr>
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</tr>
<tr>
<td>Std. Deviation</td>
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</tr>
<tr>
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<tr>
<td>Maximum</td>
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<td>2.130</td>
</tr>
<tr>
<td>Skew</td>
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</tr>
<tr>
<td>Kurtosis</td>
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<td>-0.489</td>
</tr>
</tbody>
</table>
Table 6

**Summary Table of HLM Parameter Estimates and Auxiliary Statistics**

<table>
<thead>
<tr>
<th>Reliability</th>
<th>One-Way ANOVA Model</th>
<th>Student Model</th>
<th>Exploratory School Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept ($\beta_0$)</td>
<td>0.140</td>
<td>0.042</td>
<td>0.019</td>
</tr>
</tbody>
</table>

**Fixed Effects**

**Level-1 Intercept Outcome Model**

<table>
<thead>
<tr>
<th></th>
<th>One-Way ANOVA Model</th>
<th>Student Model</th>
<th>Exploratory School Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept ($\gamma_{00}$)</td>
<td>0.018**</td>
<td>0.015**</td>
<td>0.015**</td>
</tr>
<tr>
<td>F1S8A ($\gamma_{01}$)</td>
<td>----</td>
<td>----</td>
<td>0.054</td>
</tr>
<tr>
<td>F1S8B ($\gamma_{02}$)</td>
<td>----</td>
<td>----</td>
<td>-0.019</td>
</tr>
<tr>
<td>F1S7C ($\gamma_{03}$)</td>
<td>----</td>
<td>----</td>
<td>-0.040</td>
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<tr>
<td>F1S8D ($\gamma_{04}$)</td>
<td>----</td>
<td>----</td>
<td>0.009</td>
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<tr>
<td>F1S8E ($\gamma_{05}$)</td>
<td>----</td>
<td>----</td>
<td>0.025</td>
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<tr>
<td>F1S8F ($\gamma_{06}$)</td>
<td>----</td>
<td>----</td>
<td>-0.067</td>
</tr>
<tr>
<td>F1S8G ($\gamma_{07}$)</td>
<td>----</td>
<td>----</td>
<td>0.041</td>
</tr>
<tr>
<td>F1S8H ($\gamma_{08}$)</td>
<td>----</td>
<td>----</td>
<td>0.027</td>
</tr>
<tr>
<td>F1S8I ($\gamma_{09}$)</td>
<td>----</td>
<td>----</td>
<td>-0.028</td>
</tr>
<tr>
<td>F1S8J ($\gamma_{10}$)</td>
<td>----</td>
<td>----</td>
<td>0.067</td>
</tr>
</tbody>
</table>

**Level-1 slopes:**

<table>
<thead>
<tr>
<th></th>
<th>One-Way ANOVA Model</th>
<th>Student Model</th>
<th>Exploratory School Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>BY-Self-Concept ($\gamma_{10}$)</td>
<td>----</td>
<td>0.483**</td>
<td>0.480**</td>
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<tr>
<td>BY-SES ($\gamma_{20}$)</td>
<td>----</td>
<td>0.039**</td>
<td>0.034**</td>
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<tr>
<td>FEMALE ($\gamma_{30}$)</td>
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<td>-0.077**</td>
<td>-0.078**</td>
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<td>ASIAN ($\gamma_{40}$)</td>
<td>----</td>
<td>-0.011</td>
<td>-0.010</td>
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<tr>
<td>HISPANIC ($\gamma_{50}$)</td>
<td>----</td>
<td>0.047**</td>
<td>0.051**</td>
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<tr>
<td>BLACK ($\gamma_{60}$)</td>
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<td>0.186**</td>
<td>0.193**</td>
</tr>
<tr>
<td>NATIVEAMERICA ($\gamma_{70}$)</td>
<td>----</td>
<td>0.167**</td>
<td>0.170**</td>
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</table>

**Random Effects**

<table>
<thead>
<tr>
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<th>One-Way ANOVA Model</th>
<th>Student Model</th>
<th>Exploratory School Model</th>
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</thead>
<tbody>
<tr>
<td>Level-1 effect ($r_{ij}$) variance</td>
<td>0.421</td>
<td>0.325</td>
<td>0.326</td>
</tr>
<tr>
<td>Level-2 effects ($\mu_{0j}$) variance</td>
<td>0.009**</td>
<td>0.002</td>
<td>0.001</td>
</tr>
<tr>
<td>Intra-class correlation</td>
<td>0.021</td>
<td>----</td>
<td>----</td>
</tr>
<tr>
<td>Conditional ICC</td>
<td>----</td>
<td>0.006</td>
<td>0.003</td>
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<tr>
<td>Proportion of the variance in $r_{ij}$ explained by the model</td>
<td>0</td>
<td>0.228</td>
<td>0.226</td>
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</table>
Proportion of the variance in $\mu_{oj}$ explained by the model

<table>
<thead>
<tr>
<th></th>
<th>0</th>
<th>0.778</th>
<th>0.833</th>
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</table>

Model Fit

<table>
<thead>
<tr>
<th></th>
<th>Deviance statistic</th>
<th>Number of parameters</th>
<th>Likelihood ratio test</th>
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<tbody>
<tr>
<td></td>
<td>23660.682</td>
<td>3</td>
<td>---</td>
</tr>
<tr>
<td></td>
<td>20439.414</td>
<td>10</td>
<td>3221.268**</td>
</tr>
<tr>
<td></td>
<td>20417.415</td>
<td>20</td>
<td>21.999*</td>
</tr>
</tbody>
</table>

* = significant at $\alpha = 0.05$; ** = significant at $\alpha = 0.01$; report all values to 3 decimal places
Figures

Figure 1
One possible representation of the hierarchic organization of self-concept.

Figure 1. “One possible representation of the hierarchic organization of self-concept” (Shavelson et al. 1976, p. 413)
Calculations

Unconditional Model Calculations
Intra-class Correlation Coefficient (ICC):

\[ ICC = \frac{\text{Level two variance}}{\text{total variance}} \]

\[ ICC = \frac{\tau_{00}}{\tau_{00} + \sigma^2} \]

\[ ICC = .009 / (0.009 + 0.421) \]

\[ ICC = 0.0209 \]

Student Model Calculations
Conditional Intra-class Correlation Coefficient (ICC):

\[ \text{Conditional ICC} = \frac{\text{Level two variance}}{\text{total variance}} \]

\[ \text{Conditional ICC} = \frac{\tau_{00}}{\tau_{00} + \sigma^2} \]

\[ \text{Conditional ICC} = .002 / (0.002 + 0.325) \]

\[ \text{Conditional ICC} = 0.0061 \]

Proportion of the variance in \( r_{oj} \) explained by the model

\[ \text{Variance in } r_{oj} \text{ Explained} = \frac{(\sigma^2 \text{ (unconditional model)} - \sigma^2 \text{ (conditional model)})}{\sigma^2} \]

\[ \text{Variance in } r_{oj} \text{ Explained} = (0.421-0.325)/0.421 \]

\[ \text{Variance in } r_{oj} \text{ Explained} = 0.2280 \]

Proportion of the variance in \( \mu_{oj} \) explained by the model

\[ \text{Variance in } \mu_{oj} \text{ Explained} = \frac{(\tau_{00} \text{ (unconditional model)} - \tau_{00} \text{ (conditional model)})}{\tau_{00}} \]

\[ \text{Variance in } \mu_{oj} \text{ Explained} = (0.009-0.002)/0.009 \]

\[ \text{Variance in } \mu_{oj} \text{ Explained} = 0.7778 \]

School Model Calculations
Conditional Intra-class Correlation Coefficient (ICC):

\[ \text{Conditional ICC} = \frac{\text{Level two variance}}{\text{total variance}} \]

\[ \text{Conditional ICC} = \frac{\tau_{00}}{\tau_{00} + \sigma^2} \]

\[ \text{Conditional ICC} = 0.001 / (0.001 + 0.326) \]

\[ \text{Conditional ICC} = 0.0031 \]

Proportion of the variance in \( r_{oj} \) explained by the model

\[ \text{Variance in } r_{oj} \text{ Explained} = \frac{(\sigma^2 \text{ (unconditional model)} - \sigma^2 \text{ (conditional model)})}{\sigma^2} \]

\[ \text{Variance in } r_{oj} \text{ Explained} = (0.421-0.326)/0.421 \]

\[ \text{Variance in } r_{oj} \text{ Explained} = 0.2257 \]
Proportion of the variance in $\mu_{oj}$ explained by the model

$Variance \text{ in } \mu_{oj} \text{ Explained} = (\tau_{00} \text{ (unconditional model)} - \tau_{00} \text{ (conditional model)}) / \tau_{00} \text{ (unconditional model)}$

$Variance \text{ in } \mu_{oj} \text{ Explained} = (0.009 - 0.001)/0.009$

$Variance \text{ in } \mu_{oj} \text{ Explained} = 0.8889$