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STEM PIPELINE FOR STUDENTS WITH DISABILITIES: FROM HIGH SCHOOL TO INTENTIONS TO MAJOR IN STEM

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STEM PIPELINE FOR STUDENTS WITH DISABILITIES: FROM HIGH SCHOOL
TO INTENTIONS TO MAJOR IN STEM

A Dissertation Presented

by

JOSHUA D. BITTINGER

Submitted to the Graduate School of the
University of Massachusetts Amherst in partial fulfillment
of the requirements for the degree of

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DEDICATION

To my mom, for always being supportive of my pursuit of education, even if at times it did not make sense.

To Rachel, who helped me through the ups and downs of this journey and has not held that against me.

To all of the students out there who experience disability as they move through their educational journey, both diagnosed and undiagnosed.

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I would be remiss if I did not thank my committee (Drs. Ryan Wells, Ezekiel Kimball, and Joya Misra) for their gracious support and feedback during my dissertation journey. This document shifted multiple times through our conversations, and I know that those adjustments added considerable strength to this work. Ryan has helped steer me through my doctoral education, starting from my initial application to the program.

ABSTRACT

STEM PIPELINE FOR STUDENTS WITH DISABILITIES:
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MAY 2018

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This dissertation examined the science, technology, engineering, and math (STEM) major declaration intentions of students with disabilities as they graduated high school and entered college. I used data from the High School Longitudinal Study of 2009 (HSLs:09) because data collection began in high school and followed students into college, facilitating research focusing on access. Before investigating major declaration intentions, I critiqued the definition and measurement of disability in the HSLs:09, drawing from survey research methods literature. The two subsequent analyses focused on psychological and structural components, respectively. My focus on psychological components drew from Eccles and colleagues' (1983) expectancy-value framework. This framework tapped into the valuation that students placed on math- and science-related concepts and their expectations to succeed in those fields. Structural components explored in the final analysis drew from human, cultural, and social capital theories. These three theories were at the core of Perna's (2006) model of college choice, which I

adapted to predict majoring in STEM. Both analyses utilized multiple logistic regression to create prediction models. Findings suggested that college-bound students with ADHD have higher odds of intending to pursue STEM majors, compared to students experiencing other forms of disability. Psychological and structural measures were also positively related with odds of pursuing these majors. Implications highlight avenues for enhancing STEM participation for students with disabilities, offer suggestions for improvements to future data collection efforts, and lend guidance for future researchers looking to study disability using the HSLs:09 or other secondary data.

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CHAPTER 1

INTRODUCTION

Recent postsecondary enrollment trends demonstrate positive growth for the population of students with disabilities. Estimates place the percentage of college students with disabilities around 11 to 12 percent (Snyder & Dillow, 2013; Snyder, de Brey, & Dillow, 2016), up from approximately 5 percent in 2000 (Snyder & Hoffman, 2001). The growth is likely due in large part to federal legislation allowing and protecting access to postsecondary education for these students. Section 504 of the Rehabilitation Act of 1973 established a federal mandate that persons with disabilities be allowed to attend postsecondary institutions (Peña, 2014). Accessibility was further enhanced following the passage of the Americans with Disabilities Act of 1990, providing additional civil rights protections for this population (Evans & Herriott, 2009; U.S. Government Accountability Office, 2009).

However, some have called these figures into question. The Higher Education Research Institute (2011) estimated the figure to be closer to 15 percent of full-time, first-year students having at least one disability. Subpopulation estimates of students with different types of disabilities also fluctuate depending on the data source used. Leake (2015) noted the discrepancies between the National Postsecondary Student Aid Study of 2008 (NPSAS:08) and the National Longitudinal Transition Study 2 (NLTS-2) estimates in identifying the percentage of students with different types of disabilities. Notably, the NPSAS:08 results showed that fewer than 10 percent of students with disabilities

identified as having a learning disability; however, the NLTS-2 found that almost 70 percent of students with disabilities had a learning disability.

Leake (2015) suggested that the difference between the results could be attributable to the different classifications used by each survey. The NLTS-2 used categories from the Individuals with Disabilities Education Act (IDEA), while the NPSAS:08 categories were based on the Americans with Disabilities Act (ADA). Adding support to Leake's argument, a study focusing on hearing impairments identified a range of estimates from as low as 25,000 to upwards of 400,000 (Schroedel, 2007). With such discrepancies being identified, there are considerable implications for disability researchers. Depending on the source of data used, rates of disability are likely to vary. Differences between surveys are driven by inconsistent definitions, which also lead to different types of disability being represented in research. To further unpack this issue, defining disability is discussed later in this chapter and emphasized in Chapter Two.

While the exact percentage of students with disabilities who proceed from high school to some form of postsecondary education is debated, the increase in the number of students following this path is desirable because college has been increasingly shown to result in positive earnings outcomes for everyone. Workers holding a four-year degree are poised to earn 84 percent more in their lifetimes than workers with only high school credentials (Carnevale, Rose, & Cheah, 2011). The majority of jobs already require some form of postsecondary education, and the percentage is expected to continue to rise (Carnevale, Smith, & Strohl, 2010). Employment outcomes for individuals with disabilities are troubling and perhaps the increased postsecondary enrollment of this population will help correct current inequities. Persons with disabilities have an

unemployment rate twice as high (Bureau of Labor Statistics, 2017) and have lower monthly median incomes than individuals without disabilities (Brault, 2012). Efforts to increase employment for this population are critical in order to help foster upward mobility.

This unemployment trend extends to science, technology, engineering, and math (STEM) careers, a discrepancy that emerges from differences in the pursuit and completion of related majors during postsecondary education (National Science Foundation [NSF], 2015). Limited research suggests that students with disabilities entering postsecondary education declare STEM-related majors at a similar rate as their peers without disabilities (Lee, 2011). However, Lee's (2011) study utilized two different datasets to compare students with and without disabilities. Given Leake's (2015) identification of the problematic nature of making comparisons across datasets, additional research is needed to assess Lee's findings which draws comparisons using data from a single dataset.

Obtaining a postsecondary education improves employment outcomes as well as overall quality of life for U.S. citizens (National Council on Disability, 2003; Smith, Grigal, & Sulewski, 2012; U.S. Senate Committee on Health, Education, Labor, and Pensions, 2012). Only about 20 percent of persons with disabilities who are at least 16-years-old participate in the labor force (Bureau of Labor Statistics, 2017). The rest of the population with disabilities must rely on government support for assistance.

Postsecondary education has been identified as a means by which to increase the percentage of persons with disabilities who are participating in the labor force, therefore not relying on public assistance (U.S. Government Accountability Office, 2012).

In order to encourage and facilitate college aspirations, enrollment, and pursuit of STEM degrees amongst students with disabilities, researchers and practitioners need to know more about why these students are currently choosing to enroll at postsecondary institutions and select STEM majors. This dissertation focuses on identifying the influences that lead students with disabilities to pursue STEM majors as a response to the NSF's (2015) recognition of the underrepresentation of this population within STEM fields. The analyses in Chapters Three and Four fit two separate models to predict declaration of a STEM major upon enrollment for college-bound high school students with disabilities. The first of these models explores the influence of students' attitudes, affinities, and self-assessed abilities toward math and science on their likelihood of declaring a STEM-related major. The latter model investigates the role different sources of capital play on STEM major declaration. As a guiding question for these analyses, I considered: What factors are most influential for students with disabilities as they decide to declare a STEM major upon enrolling in college?

Disability as Diversity

Around 11 - 12 percent of students in postsecondary education identify as having a disability (Snyder et al., 2016), but individuals with disabilities represent 19 percent of the U.S. population (Brault, 2012). Comparing these figures, it is clear that students with disabilities are underrepresented in higher education despite institutions historically failing to view disability as underrepresented (Linton, Mello, & O'Neill, 1995). Failing to view disability as an underrepresented identity is not unique to higher education, as social institutions continually devalue those with disabilities (Mkhize, 2015). Recent reorganization at Colorado University Boulder has made clear that the institution views

disability as a form of diversity (Aragon & Hoskins, 2017), yet students with disabilities are frequently left out of conversations pertaining to diversity (Davis, 2011; Olkin, 2002).

There are several reasons why this may be the case.

One such explanation is that students' other minoritized statuses tend to draw the most attention, with disability given little to no acknowledgment (King, 2009).

Historically, disability identification was used in coordination with other minoritized statuses in order to justify students' exclusion (Reid & Knight, 2006; Siebers, 2008;

Watson, 2003), leading to the argument that people with disabilities were more

segregated socially and educationally than any other minority group (Longmore, 2003).

In the realm of education, this exclusionary tactic lost its viability once individuals with disabilities' opportunity to participate in postsecondary education became legally

protected (Allen, 2005; Wolanin, 2005). While no longer viable, the effects of

longstanding segregation for this population are still influential on how educators and students themselves view their ability to participate in postsecondary education.

Disability is a multifaceted concept, describing a wide range of types and degrees of functionality limitations (Kim & Aquino, 2017; Linton, 1998; Kimball, Wells,

Ostiguy, Manly, & Lauterbach, 2016), despite a tendency of quantitative researchers to

compare students on the binary: disabled or not (Vaccaro, Kimball, Wells, & Ostiguy, 2015). Making comparisons in this dichotomous manner runs the risk of missing

important differences across disability types. In the aggregate, students with disabilities

may appear similar to those without disabilities in many ways; however, if researchers

embrace a multi-categorical approach they may detect numerous points of divergence for specific types of disability.

Binary representation of disability is used in a manner contrary to the continuum on which disability exists (Davis, 1995; King, 1993). That is not to say that comparisons only using binaries are unhelpful. Oftentimes binary representations are needed to answer questions related to the receipt of specific services. In education, this might be having an individualized education program (IEP) in high school or receiving disability-related accommodations in college. Additionally, the vast majority of datasets which contain disability identity information were not collected under a research design which oversampled individuals with disabilities. As a result, small sample sizes may necessitate that binary representations are used.

An additional challenge for considering disability as a form of diversity is that disability is not a stable identity and can change overnight (Siebers, 2008; Smith & Erevelles, 2004). For instance, a person could get into an accident leading to a mobility or sensory impairment. Over time, such impairments may come to pass through the body healing or rehabilitative surgery. The fluidity of disability also acknowledges a person's ability to choose whether or not to identify as having a disability. Students moving from high school to college may opt to not disclose their disability identity with their campus' disability services offices or may disassociate with the identity altogether. During college, students' decisions to identify or unidentify may also shift (Bittinger & Acquino, 2017). Because fluctuation can happen at any time, data supporting research on disability are most useful when they are longitudinal and disability identity is asked during each collection phase.

In this dissertation, I view disability as an aspect of diversity and a socially constructed identity. Following the social model of disability, as opposed to the medical

model, disability is argued to exist due to the way that society has been organized (Garland-Thomson, 2011; Weiss, 2015). When a “misfit” occurs between the individual and society, the person is deemed disabled. To the extent possible, I disaggregate results by different disability types; however, I am limited by the collection of disability identity data. These limitations are explored in-depth in Chapter Two. After addressing the limitations, I use five disability categories: learning disability, sensory impairment, mobility impairment, attention-deficit/hyperactive disorder, and developmental delay. Utilizing five categories, I was able to compare measures not only between students with and without disabilities but also across these five types.

I use person-first language throughout, referring to my population of interest as students with disabilities as opposed to disabled students. There are differing views on which label to use with this population. Disability-first (i.e., disabled student) proponents argue that placing the disabled status first highlights the oppression that society has imposed on this population (Gleeson, 1999; Priestly, 2001). Advocates of disability-first language argue that following this convention allows for self-identification (Kuo, 2015). However, opponents suggest that placing the person first (i.e., student with a disability) allows the person with a disability to reclaim power (Mkhize, 2015). I see the use of disability-first language as appropriate and powerful when taking a critical stance against institutions and their treatment of individuals with disabilities. However, my lens for this dissertation is not critical in this manner. Instead, I focus on the experience of students with disabilities to uncover reasons why they are underrepresented in STEM education, thus opt to use person-first language.

Enhancing the Workforce through STEM Education

There is a continued call to better understand the path into and through college for underrepresented populations in STEM fields (National Academies of Science, 2007; National Science Board, 2010). Understanding the reasons students decide to pursue or persist in STEM is important in order to address the insufficient number of STEM graduates that the U.S. is currently producing, despite some growth in the quantity of graduates (Commission on Professionals in Science and Technology, 2007; Lowell & Regets, 2006; U.S. Department of Labor, 2007). As a result of fewer students majoring in these fields, a gap between workforce demand and postsecondary supply exists. The percent of individuals employed in STEM fields also dropped at the beginning of the century, mirroring graduation trends (Ashby, 2006). The drop of employment in these fields is not a reflection of dwindling job opportunities. Instead, the lack of individuals pursuing related careers widens the gap in supply and demand.

The National Science Foundation (2015) highlighted people with disabilities along with women and racial minorities as underrepresented groups in STEM. However, most of the research exploring this representation has only focused on gender and race/ethnicity. Exploring the STEM pipeline beginning in high school is important because students rarely reenter after high school and their plans serve as good predictors of degree completion (Maltese & Tai, 2011; Syed, Azmitia, & Cooper, 2011; Tai, Liu, Maltese, & Fan, 2006). The underrepresentation of these populations likely contributes to the insufficient supply of STEM-ready graduates. Addressing underrepresentation could therefore alleviate the stress on the workforce introduced by lack of workers as well as create more equitable outcomes for diverse populations that want to pursue STEM.

Limited research suggested that students with disabilities were as likely as students without disabilities to enroll in STEM majors in college (Lee, 2011), yet these students continue to be underrepresented amongst STEM degree holders (NSF, 2015). If Lee's (2011) conclusions were accurate, the leak in the STEM pipeline could be located somewhere during the college years for students with disabilities. However, researchers and policymakers should refrain from enacting change based on a single, correlational study. A prominent limitation with Lee's approach was that data from two different datasets with different methodologies and operationalizations were used. While this approach was a clever way of investigating representation for students with disabilities at the time, newer data allow comparisons within a single dataset, as are conducted in this dissertation.

Identifying factors that contribute to students with disabilities remaining in the STEM pipeline can help target areas of focus to ensure that these students are as ready to pursue their interests as students without disabilities. With the projection that numerous STEM-related careers are to experience the largest growth in employment opportunities and wages (Bureau of Labor Statistics, 2009), addressing the underrepresentation and preparing students to pursue these careers stands as a promising avenue to promote social mobility among persons with disabilities. This approach is realistic, especially because more companies are viewing characteristics such as neurodiversity as desirable and advantageous (Austin & Pisano, 2017; Parmar, 2017).

Several explanations for the continued underrepresentation of persons with disabilities in STEM fields and careers have been offered. One study suggested that the lower participation rates of students with disabilities in high school activities leads to

being less involved in STEM career preparation (Eriksson, Welander, & Granlund, 2007). Without this career preparation, these students are at a disadvantage moving onto further education or into the workforce. Students with disabilities do not have access to role models in STEM fields (Alston, Bell, & Hampton, 2002), negatively influencing their own interest in such majors. These students are less likely to see someone like them holding positions that they may aspire to, particularly because so many disabilities are not readily apparent.

Parents and teachers may hold the misperception that these students are incapable of pursuing STEM careers, urging students to pursue other fields (Alston & Hampton, 2000; Alston, Hampton, Bell, & Strauss, 1998). The possibility that teachers may view them in this manner may lead some students with disabilities to refrain from disclosing their disability identity. Even when teachers are receptive to students with disabilities' desires to pursue STEM education, they often lack necessary skills to meaningfully include these students in the curriculum (Bargerhuff, Cowan, & Kirch, 2010; Rule, Stefanich, Haselhuhn, & Peiffer, 2009; Todd, 2008). Relevant skills may cover inclusive language use or adapting teaching strategies to appeal to a variety of learning styles.

High School Data to Study the STEM Pipeline

Chapters Two through Four employ secondary data analysis using the High School Longitudinal Study of 2009 (HSLs:09), sponsored by the National Center for Education Statistics (NCES). These data are the latest in a lengthy history of longitudinal studies which the NCES has conducted beginning in high school and following students through postsecondary education. The majority of the data in the HSLs:09 pertains to the high school experiences of students across the country; however, in 2013 a brief update

was conducted to capture high school transcript and college enrollment information (Ingels et al., 2015).

Data collection for the HSLs:09 began in the fall of 2009, involving over 900 randomly selected public and private high schools (Ingels et al., 2015). From these schools, students were randomly sampled, resulting in a stratified random sample. Students were the primary unit of analysis. Parents, principals, math and science teachers, and each schools' head counselors were surveyed to provide contextual and supplementary information. During the base-year and first follow-up, students completed assessments of math proficiency and surveys capturing a broad range of data, including expectancies, valuations, and behaviors pertaining to STEM. The numerous STEM-related questions allow me to explore outcomes from two different theoretical perspectives in this dissertation.

During the base-year of data collection, 26,310 students were sampled, with 21,440 respondents (Ingels et al., 2015). Of these respondents, 18,610 also responded during the first follow-up. The sample was nationally representative of high school students who were enrolled in 9th grade in the fall of 2009. Previous NCES-sponsored high school studies "freshened" the sample during each wave to allow for generalizability outside of the cohort of students enrolled in high school at the beginning of the study. However, for the HSLs:09, the NCES refrained from "freshening" the sample, restricting generalizability to the initial 9th grade cohort.

Utilizing these data, I focus on the pre-college factors influencing students with disabilities' decisions to pursue STEM-related majors. Results from my analyses in Chapters Three and Four provide starting points for working to ensure that students with

disabilities who are interested in STEM fields are best equipped to pursue these majors in college. Additionally, interventions can be designed to foster interest in these fields during high school to help address underrepresentation. High school data are particularly helpful when studying topics related to college access. For students with disabilities in particular, using high school data may even be preferred over college data because of the number of students who unidentify as having a disability as they enter college (Litner, Mann-Feder, & Guerard, 2005).

Defining Disability

Definitions of disability vary widely, and, as mentioned previously, such variations can have significant impacts on research. While Chapter Two delves into a deeper discussion of disability definitions and their implications, I highlight a few definitions here. Three main sources of disability definitions were important for this dissertation: the IDEA, ADA, and HSL:09.

The IDEA (2015) protects the educational rights of primary and secondary students and specifies thirteen impairment types which qualify for special education services if they impact a student's ability to learn: a) specific learning disability, b) autism spectrum disorder, c) emotional disturbance, d) speech or language impairment, e) visual impairment, f) deafness, g) hearing impairment, h) deaf-blindness, i) orthopedic impairment, j) intellectual disability, k) traumatic brain injury, l) other health impairment, and m) multiple disabilities.

College students with disabilities have their educational rights protected by the ADA. According to the ADA, a person is considered to have a disability if they have "a physical or mental impairment that substantially limits one or more major life activities,"

they have “a record of such an impairment,” or they are “regarded as having such an impairment” (ADA Amendments Act, 2008, Sec 12102).

The HSLS:09 followed neither of these definitions; instead asking parents if their children had any of the following conditions: a) specific learning disability, b) any developmental delay that affected their ability to learn, c) autism, Asperger’s Disorder, pervasive developmental disorder, or other autism spectrum disorder, d) hearing problems or vision problems that cannot be corrected with glasses or contact lenses, e) bone, joint, or muscle problems, f) intellectual disability or mental retardation, and/or g) attention deficit disorder or attention deficit hyperactive disorder (Ingels et al., 2015). Questions asking about the degree that students experienced difficulty engaging in several tasks were also included in the data; however, these are not used for identifying students as having a particular disability in this dissertation.

Choosing the Appropriate Metaphor

The prevailing metaphor when discussing STEM education is that of the STEM pipeline (e.g., Blickenstaff, 2005; Metcalf, 2010; 2014). This metaphor is often depicted as a pipeline that moves from high school, through college to graduation, and eventually to employment in a STEM field, with only a few drops of water falling from the end of the pipeline to signify the small number of students who make it through the complete pipeline (Cannady, Greenwald, & Harris, 2014). This visual is depicted in Figure 1 below. A key characteristic of this visual is that as students move through the pipeline, the pipe itself gets progressively smaller and leaks at each connection.

Depicting students’ journeys toward STEM in this manner is problematic because it implies that students must take one trajectory from high school to graduation. This

singular trajectory approach does not match the actual paths that approximately half of those in STEM careers end up taking (Cannady et al., 2014). As students leak out of the pipeline in the visual, they are unable to re-enter. An additional implication is that the leaks in the pipeline are actually a bad thing. College major fluctuation occurs across all fields as students are exposed to new ideas.

Dissenters to the pipeline metaphor are drawn to the pathway metaphor which addresses several of the shortcomings of the pipeline approach. A pathway allows students to freely enter and leave at any point during their lives. For instance, a student may graduate from high school, move into the workforce, begin taking classes part-time to earn an Associate's while continuing to work, quit their job to pursue a Bachelor's, and then return back to the workforce. Another student could have a completely different path. These transitions are expected and encouraged; however, they make creating a streamlined depiction of an education trajectory that applies to the majority of students difficult.

I opt for the pipeline metaphor as opposed to a pathway. This choice is beneficial to my studies because the metaphor is so commonly used when exploring STEM outcomes that little explanation is required. Additionally, the pipeline metaphor is clearer than the pathway metaphor. Because of the clarity, the pipeline can be simply visualized as is shown in Figure 1. Comparatively, describing a pathway is rather challenging because of the nature of allowing multiple entry and exit points. Exploring the ways that researchers have attempted to explain the pathway metaphor even convinced me that the pathway is actually more akin to a road than a path (Branch, 2016). One of the purposes

of using a metaphor when talking about STEM education is for ease of explanation, something that I became convinced that a pathway metaphor would not facilitate.

A pathway metaphor has the advantage of flexibility of application, able to be used during high school or any point during or after postsecondary education. However, I am only interested in the movement of students from high school into STEM majors as they reached college. My samples are composed of 9th grade students, and, as can be seen in Figure 1, these students are assumed to be in the pipeline by default. My analyses are not concerned with students re-entering the STEM pipeline; instead, they are focused on the retention of students in the pipeline, ultimately leading to the decision to utilize the well-known pipeline metaphor throughout my dissertation. Because much of disability research in this area is in its infancy, a pipeline approach also allows me to focus on structural characteristics leading to leaks as opposed to societal pressures that are more readily studied by a pathway metaphor.

Figure 1. The Leaky STEM Pipeline



Source: NCES Digest of Education Statistics; Science & Engineering Indicators 2008

Purpose of this Dissertation

In the preceding text, I emphasized the importance of considering disability definition when researching students with disabilities. Based on this emphasis, Chapter Two fully considers the definitions employed in the HSL:09. This chapter not only expands upon my previous argument, but also influences the way I operationalize disability in Chapters Three and Four. These latter two chapters are similar in the sense that I investigate the same outcome for college-bound students with disabilities: intention to declare a STEM major upon college enrollment. Each of these chapters applies a different model utilized throughout educational research but which has not been used to study students with disabilities in particular. Chapter Three explores psychological factors influencing STEM majoring while Chapter Four focuses on structural constructs. These two perspectives are useful when considering my overarching question: What factors are most influential for students with disabilities as they decide to declare a STEM major upon enrolling in college? Below, I discuss the purpose of each chapter in greater detail.

Chapter Two: Disability in Education Research Using National Datasets:

Definition and Measurement Considerations

Before engaging in a project, researchers should spend time understanding and assessing their data. Doing so can be helpful in determining the feasibility of exploring particular questions and provide insight into potential measurement hurdles to overcome and/or acknowledge. In Chapter Two, I spend time exploring the disability data from the HSL:09, noting how the data were collected and critiquing measures where necessary. I offer descriptive statistics and comparisons to detail proportions of students with each

type of disability included on the survey, construct a validity argument, and discuss missing data concerns. I reflect back on my assessment of the HSLS:09 and offer suggestions to future researchers using this dataset in particular as well as other secondary data to study students with disabilities.

An additional purpose of this chapter was to extend Leake's (2015) critique of disability measurement in the NPSAS:08, which focused on postsecondary data. There was a clear lack of consideration of disability measurement within datasets used for studying matters of postsecondary transition and access in the educational literature (i.e., including both secondary and postsecondary data). Leake's critique also lacked proper consideration of the NPSAS:08 in light of survey research methods. To address these shortcoming, I highlight several important ways that the questions from the HSLS:09 do not abide by survey research best practices and the potential implications from these divergences. Continuing to draw from the survey research literature, I offer revisions for future iterations of this survey that can be used by educational survey designers at large.

Chapter Three: Influence of STEM Valuation and Success Expectations on Major Declaration for Students with Disabilities

Utilizing Eccles and colleagues' (1983) expectancy-value framework as an analytic lens, I investigate the role that psychological constructs play in students' intentions to declare STEM majors upon college enrollment. Within this framework, I focus on subjective task value concepts and students' expectations for success. In Chapter Three, both task value and success expectations relate to math and science subjects. This chapter is modeled after previous work using the HSLS:09 to study expectancy-value concepts for high-achieving high school students (Andersen & Ward, 2014). This

framework has been used extensively in education research, but previous research has lacked consideration of disability. Chapter Three helps to bridge this gap.

A draw of using the HSLs:09 to study the influence of the expectancy-value framework on college major intentions is that the framework was taken into consideration during the design of the survey. As a result, I am able to include all aspects of this framework: a) math and science attainment values, b) math and science utility values, c) math and science intrinsic values, d) non-financial STEM cost, and e) math and science self-efficacy. To identify measures to represent these concepts, I draw from the aforementioned research and the technical documentation for the dataset. Using these measures, I conduct factor analyses and investigate differences across disability types. Calculated factors are then carried forward to build a logistic regression model to predict STEM majoring intentions. I also test interaction terms between different types of disability and expectancy-value factors as well as race and gender.

Chapter Four: Influence of Multiple Forms of Capital on STEM Major Intentions for Students with Disabilities

In Chapter Four, I draw from human, cultural, and social capital theories to explore the structural influences on high school students' intentions to declare STEM-related majors upon college entry. These three theories were located at the core of Perna's (2006) college choice model, and I adapt this model to guide variable selection and model building. Manifestations of these three types of capital are commonly employed in research but are often not explicitly identified as representing these theories. Through a focused literature review, I highlight research suggesting that such manifestations play an influential role in major declaration. During the adaptation

process, I reconstruct the college choice model to more appropriately analyze college major choice. A draw of adapting Perna's model is the consideration of context and the accounting for structural characteristics of the high schools that students attended.

The revised framework contained the two innermost layers of Perna's (2006) framework, encompassing measures of capital and school characteristics. Because I include measures pertaining to school-level characteristics, an analytic approach accounting for the nested nature of the data is desirable. Sources of capital are compared across disability types to identify differences that can be targeted for intervention. I attempt to utilize hierarchical generalized linear modeling to address the nesting of the data but ultimately move onto multiple logistic regression modeling after analyzing model diagnostics.

CHAPTER 2

DISABILITY IN EDUCATION RESEARCH USING NATIONAL DATASETS: DEFINITION AND MEASUREMENT CONSIDERATIONS

At the start of many journal articles focusing on college students with disabilities, authors cite the percentage of postsecondary attendees who self-identify as having some form of impairment according to the most recent iteration of the Digest of Education Statistics. This statistic is used to demonstrate the importance of considering disability as an influential and relevant demographic characteristic in various studies about postsecondary outcomes. The Digest relies on data from the National Postsecondary Student Aid Study (NPSAS), and the most recent estimate suggested that about 11 percent of college students have at least one disability (Snyder, de Brey, & Dillow, 2016). While this statistic is important to point out, especially to the larger community of researchers who are not aware of growing proportions of students with disabilities in higher education, it is also important to understand how this figure originates.

Two primary components drive disability-related figures such as the statistic cited above: definition and measurement. The consensus among researchers measuring disability through survey-based research is that no single definition of disability exists; instead, definitions used by survey writers tend to be purpose-specific (Altman, 2001). Outside of survey research, a plethora of definitions are offered from government agencies such as the Centers for Disease Control and Prevention (CDC) to nonprofit organizations such as the Association on Higher Education and Disability (AHEAD). Even within policies protecting the educational rights of students with disabilities such as

the Individuals with Disabilities Education Act (IDEA, 2015) and the Americans with Disabilities Act (ADA, 2008), the definitions used to define disability and impairment differ. Purpose-driven definitions and variant measurement techniques potentially limit the usability of data for multiple projects and researchers.

Measurement issues behind disability-related figures must be considered to assess their strength and potential validity; however, limited research exists that tackles disability measurement in the field of education. Further, higher education research focusing on disability is seldom published outside of disability-specific outlets (Leake & Stodden, 2014; Peña, 2014), limiting the number of scholars taking part in discussions of disability measurement. Critical quantitative researchers have taken note of the data-related challenges faced by researchers studying disability (e.g., Vaccaro, Kimball, Wells, & Ostiguy, 2015). Approaching research from a critical quantitative lens necessitates that researchers carefully consider the data they are using to answer their research questions, motivating the approach to the present chapter. If not careful, researchers are in positions to further the oppression and marginalization of persons with disabilities through their work. For instance, a researcher underestimating the proportion of students with disabilities and suggesting that too many resources are devoted this population or making generalizations about these students using data not representative of students with disabilities.

Leake (2015) discussed the problematic nature of data gathered for the NPSAS, drawing comparisons between those data and those captured for the second National Longitudinal Transition Study (NLTS2). Using the High School Longitudinal Study of 2009 (HSL:09), this chapter extends Leake's critique to data pertaining to secondary

education. In his critique, Leake (2015) suggested that data from the Education Longitudinal Study of 2002 (ELS:02), the predecessor of the HSLs:09, were more accurate than NPSAS data. Higher education researchers studying matters of access are particularly well served by data from the HSLs:09 because the dataset contains information about secondary and postsecondary experiences. In addition to assessing the validity of the HSLs:09 data, I critically considered the measurement of disability according to survey research best practices and posited implications and suggestions extending beyond the HSLs:09.

Models of Disability

How society chooses to define disability has profound implications on the lived experiences of individuals with disabilities. Societal definitions shift over time as understanding of disability changes. As a result, numerous models of disability have gained traction throughout history, reflecting these definitional shifts (Drum, 2009). Understanding of disability is influenced by societal factors such as economic conditions, cultural norms, and political viewpoints (Meade & Serlin, 2006). Within higher education, different models introduced assumptions about disability which served to limit or expand access to postsecondary education for individuals with disabilities (Evans, Broido, Brown, & Wilke, 2017). The existence of numerous models of disability poses measurement challenges because subscription to different models has resulted in disagreement over definitions of disability (Scotch, 2009). While several models of disability exist, I focused on the two that currently dominate quantitative research efforts: medical and social.

The medical model is typically seen as the dominant understanding of disability. At its core, this model adopts the notion of a “typical” or “normal” person. When a person deviates from this notion, they are deemed to have a disability. The deviation is a manifestation of a problem nested within an individual that has been caused by some failure of the body (Olkin, 1999). Individuals with disabilities are then seen as incapable of fully functioning as humans and in need of medical care to cure their ailments (Siebers, 2008). Researchers attempting to measure disability under the medical model are likely doing so in order to quantify the need for medical resources or connect individuals with health care.

While the medical model understands disability to result from problems within individuals, the social model views disability as resulting from restrictive environments. Supporters of this model see disability as being a social construct (Llewellyn & Hogan, 2000). Because disability is located in the social environment, individuals may experience limitations in one setting but not in another (Marks, 1999). In this way, disability identity becomes extremely fluid. Researchers attempting to measure disability under the social model focus on the ways the environment impairs individuals, such as lack of wheelchair ramps or lack of alternate text for digital images. The medical and social models view disability very differently, leading to differential data needs for proponents of either. Such differing data needs produce divergent definitions and measurement approaches.

Disability Definitions

Categories of Definitions

According to research by Grönvik (2007), disability definitions fall into five general categories: a) subjective, b) functional, c) administrative, d) social, and e) relational. Use of *subjective* definitions requires individuals to self-identify as having specific impairments (e.g., Do you have a learning disability?). Questions applying *functional* definitions ask about an individual's functional limitations in a binary sense (e.g., Do you have trouble climbing stairs?). If respondents answer in the affirmative to at least one question, they are categorized as having a disability (Abberley, 1992).

Administrative definitions classify individuals as having a disability if they receive disability-related benefits or services (Hedlund, 2004; Molden & Tøssebro, 2010). This definition category has been referred to as official recognition of disability (Ravaud, Letourmy, & Ville, 2002). In education, administrative definitions are used to determine eligibility for individualized educational programs (IEPs) in K-12, protection under Section 504, and receipt of accommodations from disability resources offices at postsecondary institutions.

Subjective, functional, and administrative definitions are commonly used by those operating according to the aforementioned medical model of disability. As a result, these types of definitions implore individuals to identify problems within themselves limiting their ability to engage in life activities such as learning. Wording of questions using these definitions are commonly phrased with "do you have" Opposed to the first three, social and relational definitions are based on the social model of disability. Under *social* definitions, disability arises due to barriers encountered in the environment. *Relational*

definitions entail the interaction between individuals with functional limitations and restrictive environments (Shakespeare, 2005). Question wording for social and relational definitions focuses on the experiences and interactions that individuals have with various aspects of their environment. This focus recognizes the origin of disability as being external to individuals and not something that they “have.”

Scope of Definitions

Survey writers tend to define disability either broadly or narrowly. Broad definitions serve to emphasize the impact of the environment on creating disability (Schneider, 2009). Questions utilizing broad definitions may focus on identifying aspects of the environment that are not accessible for individuals in an effort to target future modification efforts (e.g., What difficulties do you experience while taking notes during course lectures?). Conversely, narrow definitions characterize disability as a medical problem that needs to be identified and/or eligibility criteria for disability-related programs and services.

Thinking of disability theoretically, most disability researchers operate in terms of broad definitions (i.e., social or relational); however, there are few survey operationalizations of these measures (Molden & Tøssebro, 2010). In general, definitions used in survey-based research tend to lag behind theoretical developments (Altman, 2001). Slow adaptation may, in part, be practical so that survey instruments are not designed to measure disability in a new theoretical fashion that will be replaced or revised in short time. For longitudinal studies, alteration of existing measures is difficult – changing measures reduces researchers’ ability to evaluate differences and changes over time.

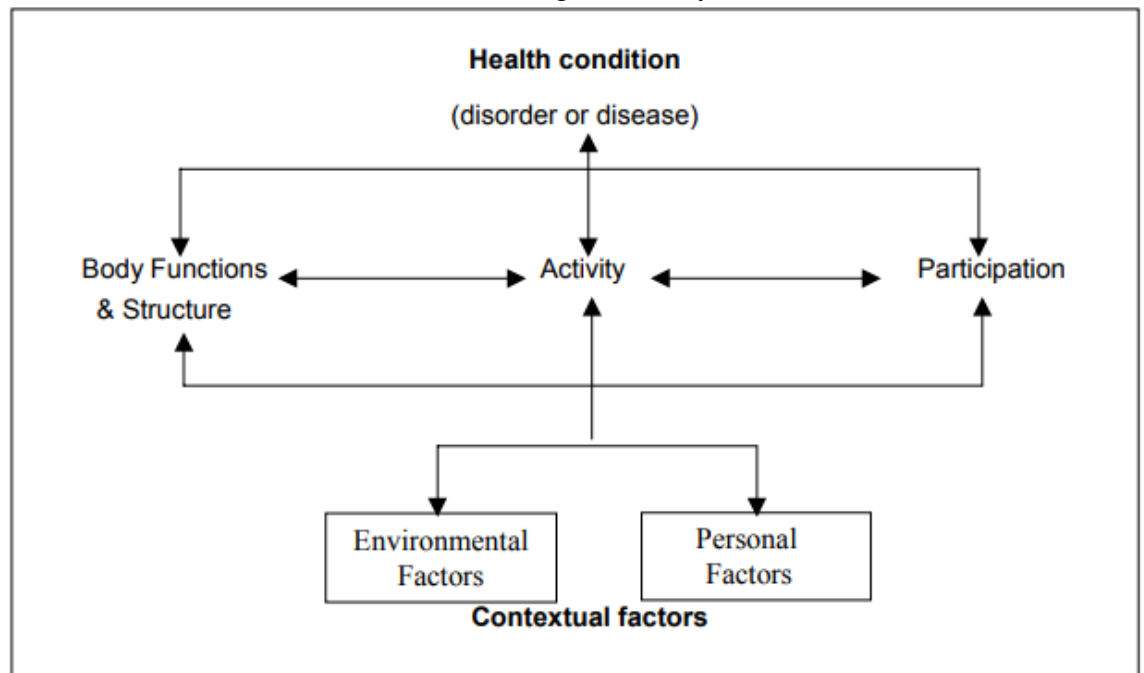
Sources of Definitions

Further complicating defining disability in survey research are the definition variations outlined by laws and organizations. During their K-12 years, students' educational rights are protected through the IDEA. This Act specifies thirteen impairment types that qualify for special education services if they limit a student's ability to learn: a) specific learning disability, b) autism spectrum disorder, c) emotional disturbance, d) speech or language impairment, e) visual impairment, f) deafness, g) hearing impairment, h) deaf-blindness, i) orthopedic impairment, j) intellectual disability, k) traumatic brain injury, l) other health impairment, and m) multiple disabilities (IDEA, 2015). The IDEA requires the collection and reporting of detailed data on students with disabilities, prompting the adoption of data collection approaches. Students are also protected under Section 504 of the Rehabilitation Act of 1973 during this time, as well as once they graduate and move into the workforce or pursue additional education. Section 504 offers protection from discrimination to any students with disabilities, including students who do not have one of the thirteen disability types identified by the IDEA. As students move into postsecondary life, the IDEA jurisdiction is replaced by the ADA.

Postsecondary education institutions must abide by the ADA when determining students' eligibility for disability-related accommodations (National Joint Committee on Learning Disabilities, 2007). This Act was modeled after Section 504 and extended its protections to additional entities such as private institutions. According to the ADA, a person is considered to have a disability if they have "a physical or mental impairment that substantially limits one or more major life activities," they have "a record of such an impairment," or they are "regarded as having such an impairment" (ADA Amendments

Act, 2008, Sec 12102). Section 504 also defines disability in this manner. This definition suggests the need to capture disability identification in a more nuanced fashion than as solely a binary measure in order to determine whether or not an individual is *substantially* limited in their activities. The ADA does not delimit different disability types; researchers looking to see how individual disabilities are defined instead consider definitions offered by sources such as the CDC, Diagnostic and Statistical Manual of Mental Disorders, and AHEAD.

Figure 2. International Classification of Functioning, Disability, and Health



Similar to the ADA, the World Health Organization (WHO) adopts a broad definition of disability which encompasses impairments, limitations, and restrictions (2011). The WHO's view on disability includes both the medical and social models mentioned previously, embodied in its bio-psycho-social model. Figure 1 contains a visual depiction of the International Classification of Functioning, Disability, and Health (ICF), which served as the framework for the WHO's (2011) report on disability. This

model offers a holistic view of disability which encompasses the interaction between personal and environmental factors, health conditions, bodies, activity limitations, and participation restrictions. By taking into consideration the interaction of these factors and characteristics, the potential fluidity of disability is captured. The broad definition adopted helps to establish disability as a universal experience as opposed to one only experienced by a small, marginalized group of people (Schneider, 2009) and is used widely in both research and practice (Jelsma, 2009).

Disability Measurement

How disability is defined has significant implications for the resulting measurements and can become complex to ask about on typical survey instruments (Molden & Tøssebro, 2010; Schneider, 2009). The majority of survey-based research capturing information about disability has utilized the medical model of disability (Baglieri & Shapiro, 2012). Not surprisingly, medical and epidemiological research largely uses data collected from medical model definitions (McDermott & Turk, 2011). Conceptualizing of disability according to the medical model has been seen as the most appropriate method to identify individuals in surveys and censuses, while social and relational models provide researchers with lenses to consider how social institutions effectively establish disability (Bengtsson, 2008, as cited in Molden & Tøssebro, 2010). The medical model is likely seen as the appropriate tool because of the readily apparent self-identification questions that can be formulated (e.g., Do you have a vision impairment?). Employing a social or relational model makes asking about disability challenging, especially if researchers are interested in a range of contexts. Treating

disability as more than simply a physical or mental impairment is still in its early stages in survey research (Cappa, Petrowski, & Njelesani, 2015).

Approaches to Measurement

A report from the International Centre for Evidence in Disability (2014) identified four standard approaches to measuring disability. Individually, each of these approaches followed the medical model, assuming that disability was rooted within individuals. However, taken together, the combination of all approaches can be used to follow the view of disability outlined by the ICF. The first approach, a common yet rudimentary technique, is through *direct questioning* where respondents are asked about disability in a dichotomous sense (e.g., Do you have a disability?). Direct questioning on a survey can lead to underreporting due to reasons discussed below. A second method of measuring disability is through *self-reported activity limitation* (e.g., Do you have difficulty walking or climbing stairs?). While resultant measures are more likely to capture a spectrum of ability, the data are more challenging to use for planning or assessment purposes. At times, administrators or policymakers need measures that can be easily quantified to depict the number of individuals with disabilities, and this method does not always easily provide that.

Another approach is referred to as *self-reported participation restriction* (e.g., Do you have difficulty maintaining social relationships?). While these questions are useful to establish difficulty participating in life activities, they do little to identify the cause of such difficulties. Both self-report approaches (i.e., activity limitation and participation restriction) also necessitate the inclusion of numerous survey items, increasing respondent burden particularly for those with limitations and restrictions (Dillman,

Smyth, & Christian, 2014). Survey writers seeking to avoid adding numerous questions may include survey items which ask multiple questions at once in order to avoid overburdening respondents, leading to confusion about how to respond (e.g., How much difficulty do you experience when trying to concentrate, remember, or make decisions?). Finally, individuals can undergo *clinical screening for impairments* (e.g., completing an instrument designed to detect an attention disorder). Clinical screenings only tap into one potential aspect of disability, are quite resource intensive, and are a significant burden to respondents (International Centre for Evidence in Disability, 2014).

Effects of Operationalization

While asking about disability in multiple ways on a survey allows researchers to view disability broadly and follow the ICF model, disability operationalization tends to follow a single approach. Differing operationalization of disability between countries, states, and organizations has been identified as a potential explanation for the variation in reported disability rates (Brandt, Ho, Chan, & Rasch, 2014; Molden & Tøssebro, 2010). An analysis of survey instruments in Norway revealed a disability rate ranging from 7 to 30 percent depending on definitions used (Tøssebro & Kittelsaa, 2004). Applying Grönvik's (2007) five categories of disability to a single dataset, Molden & Tøssebro (2010) reported disability rates ranging from 10 to 25 percent. Of these five categories, the administrative definition overlapped with the others the least. The divergence of the administrative data is troubling considering that institutions often rely on such data to make decisions about resource need and allocation. Over the course of a decade of disability rate measurement in the U.S., the 2015 American Community Survey reported 12.6 percent, the 2014 Current Population Survey indicated 8.4 percent (Cornell

University Employment and Disability Institute, 2017), and the CDC reported 22 percent of individuals living within community settings experienced a form of disability (Peacock, Iezzoni, & Harkin, 2015).

Surveys employing medical model definitions often capture disability narrowly as a binary measure – measuring only a disability’s presence or absence (Cappa et al., 2015). Resulting measures create an incomplete picture of disability in society. Only individuals with the most severe limitations are identified as having disabilities through the medical model, neglecting those with lesser degrees of impairment (Cappa et al., 2015; Schneider, 2009). This pattern was apparent during testing of a Canadian instrument which used the terms “long-term,” “disability,” and “handicap” (Langlois, 2001). Using narrow definitions to measure disability leads to further marginalization of this population. Marginalization through measurement occurs because the narrow definitions depict disability as infrequent (i.e., small percentages) and only having very severe impacts on activity. Governments work to exclude individuals with disabilities from society through placement in special housing and removal from the workforce (Schneider, 2009) and educational institutions place students in separate classrooms and restrict access to advanced coursework.

Researchers who subscribe to the social model are commonly interested in barriers experienced by those with disabilities (McDermott & Turk, 2011). Focusing on barriers is a difficult task in a survey environment where new ways of measuring disability are only beginning to be tested. The emergent bio-psycho-social model is beginning to shift measurement of disability to address the limitations of the medical model approach by layering in aspects of the social model of disability. The bio-psycho-

social model views disability as stemming from interactions between individuals with impairments and environmental obstacles which restrict their ability to fully participate in society (WHO, 2001). Additionally, disability is increasingly being viewed as a fluid identity (Riddell & Weedon, 2014). Measurement of such a dynamic identity characteristic needs to be captured repeatedly over time to account for changes in ability and environment (de Leon & Freedman, 2015).

Survey Research Methods

While terms and definitions can lead to underreporting, perceived stigma also poses a threat to accurately capturing data on disability. In communities where the perceived stigma of having a disability is higher or a lack of acceptance is present, respondents may be less likely to accurately identify themselves or family members as having a disability or impairment (Cappa et al., 2015). If respondents perceive stigma around disability, they may be reluctant to disclose their disability-related identity due to social desirability bias. Survey research methodologists understand social desirability to impact respondents who feel that certain answers may be socially unacceptable and seek to avoid social disapproval by altering their responses, thereby introducing bias into the collected data (DeMaio, 1984; Paulhus, 2002; Tourangeau, Rips, & Rasinski, 2000). Care must be taken during question writing and design in order to reduce the potential elicitation of desirability bias.

One approach to reducing the threat of social desirability bias is the use of proxies to complete survey batteries as opposed to asking individuals to self-report (Mathiowetz, Brown, & Bound, 2001; Tourangeau et al., 2000). Using proxies to ask about disability might lead to surveying parents and/or teachers instead of students themselves. Doing so

can be helpful if the chosen proxies are more informed about the survey topic because they are better equipped to provide accurate responses than the target individuals. The use of proxies can also reduce survey rates of nonresponse and administration costs by asking a single proxy to report on the actions of multiple individuals (Todorov & Kirchner, 2000). However, proxy reports are not without their problems.

Proxy respondents are likely to provide information for another target individual as well as completing a survey themselves (Moore, 1990). This would be the case for teachers completing a survey about themselves while also being asked to report disability experiences of their students. Considering the relatively few education surveys that focus only on students with disabilities, this additional burden for proxies seems probable. Further, proxies may complete requests without complete information and interpret the questions differently than the target individual(s) would (Tourangeau et al., 2000). The fallibility of proxies challenges the assumption that they are able to provide the same information as the intended respondents (Todorov & Kirchner, 2000). Proxies may be useful when asking about diagnosed disabilities for young respondents, but moving beyond simple indication of diagnoses into recognition of degree of difficulty faced during an individual's daily activities is likely to be less useful. National health surveys utilizing proxies have been shown to suffer from systematic bias, calling into question national disability statistics from such sources (Todorov & Kirchner, 2000).

Assessing HSLs:09 Measures of Disability

Source of Data

The rest of this chapter considers the strength of the disability-related measures in the HSLs:09, applying the concepts discussed above. While Leake (2015) examined the

postsecondary disability data available through the NPSAS, consideration was not given to disability data for studying the transition to postsecondary education. The HSLs:09 was sponsored by the National Center for Education Statistics (NCES), and was the latest in a lengthy history of longitudinal studies conducted beginning in high school and following students through postsecondary education (Ingels et al., 2015). These data are important because they allow researchers to follow students with disabilities as they move from the protections under the IDEA to those under the ADA. Accordingly, definition and measurement of disability are critically important to ensure the viability of the data for longitudinal analyses such as comparing secondary and postsecondary educational experiences or tracking changes in disability identification during students' educational journeys.

Data collection for the HSLs:09 began in the fall of 2009, involving over 900 randomly selected public and private high schools (Ingels et al., 2015). Students were randomly sampled from these schools, resulting in a stratified random sample. Students were the primary unit of analysis, and parents, principals, math and science teachers, and each schools' head counselors were surveyed to provide contextual and supplementary information. During the base-year of data collection, 26,310 students were sampled, with 21,440 respondents (Ingels et al., 2015). The sample is nationally representative of high school students who were enrolled in 9th grade in the fall of 2009. The student-level disability-related measures were primarily captured using parents as proxies during the base-year of data collection. Two additional measures were captured through administrative data (i.e., individual education programs [IEPs]) and included in the student survey during the base-year. Only the base-year of data was used for the current

analysis, drawing from the parent and student instruments, because only administrative disability data were captured during the first follow-up. Descriptive statistics were used to explore relationships between variables, using only complete cases.

Approach to Considering Validity

When considering the validity of elements of the NCES instrument, I drew from work by Messick (1989) and Kane (1992, 2001). Specifically, I evaluated the construct validity of the disability batteries. Previously, construct validity was understood to be one type of validity that researchers could choose to demonstrate. Current thinking in educational research supports construct validity as an overarching, general approach to validity work (Cook & Beckham, 2006; Porter, 2011). Messick (1989) outlined five sources of evidence to evaluate an instruments' construct validity: a) content, b) response process, c) internal structure, d) relations to other variables, and e) consequences. These sources of evidence were meant to be used to investigate validity for entire instruments, so not all of the concepts applied to my consideration. The three that I focused on were content, response process, and relations to other variables. I used these three sources of evidence to construct a validity argument (Kane, 1992; 2001) assessing whether or not the disability measures can be interpreted as intended.

Questions about Conditions

Complete question text and response count information for the disability questions on the base-year parent survey can be found in Tables 1 and 2. Table 1 lists seven "conditions" that students might have had, which clearly approached disability from a medical model perspective. The questions asked about conditions, which are typically associated with health-related matters. Presented with subjective definitions,

parents were asked to indicate the existence of conditions, with no consideration of degree of difficulty. These questions utilized narrow definitions of disability and direct questioning. Considering that these questions pertained to high school students, one would imagine that the types of disabilities included would reflect the qualifying types found in the IDEA. However, this was not the case, and the listed conditions did not seem to be modeled after any relevant classification system.

Table 1. Question Text for Binary Measures from Parent Survey

Question Text	Variable Name	n	Item Nonresponse
Has a doctor, health care provider, teacher, or school official ever told you that [your 9 th -grader] has any of the following conditions?			
Specific Learning Disability	P1SLD	1,550	1,270
Any developmental delay that affects [his/her] ability to learn	P1DD	760	1,290
Autism, Asperger's Disorder, pervasive developmental disorder, or other autism spectrum disorder	P1AUTISM	190	1,310
Hearing problems or vision problems that cannot be corrected with glasses or contact lenses	P1EAREYE	450	1,270
Bone, joint, or muscle problems	P1JOINT	450	1,280
Intellectual disability or mental retardation	P1INTELLECT	120	1,310
Attention Deficit Disorder or Attention Deficit Hyperactive Disorder, that is, ADD or ADHD	P1ADHD	1,640	1,300
Does [your 9 th -grader] currently receive Special Education Services? Students receiving these services often have an Individualized Education Plan (IEP)	P1SPECIALED	1,460	1,240

Is [your 9 th -grader] currently taking medication for ADD or ADHD?	P1ADHDMED	830	1,240
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Note. Estimates weighted using W1STUDENT weight.

Table 2. Question Text for Difficulty Measures from Parent Survey

Question Text	Variable Name	“A Lot of Difficulty” n	“A Little Difficulty” n	Item Nonresponse
Compared with other 9 th graders, would you say [your 9 th -grader] experiences a lot, a little, or no difficulty in the following areas?				
Learning, understanding, or paying attention	P1LEARN	890	3,600	1,300
Speaking, communicating, or being understood	P1SPEAK	270	1,800	1,290
Feeling anxious or depressed	P1MOOD	480	2,570	1,320
Behavior problems, such as acting-out, fighting, bullying, or arguing	P1ACTOUT	450	1,670	1,280
Making and keeping friends	P1FRIEND	330	1,450	1,290

Note. Estimates weighted using W1STUDENT weight.

The majority of disability-related measures were asked of parents about their children. The first battery of questions asked parents about whether they had been informed by a doctor, health care provider, teacher, or school official that their child had any of several conditions. From a survey research perspective, the question was problematic for a couple of reasons. First, the authority of all four types of informants were treated as identical by asking about them all at once; however, only a doctor or other licensed health care provider is able to diagnose an individual with any of the

conditions asked about in the question. Teachers and other school officials are likely not trained to recognize signs of disability or the conditions referenced by the questions. Additionally, just because a teacher or school official told a parent that a student might have one of the conditions does not mean that the parent pursued diagnosis. The question is therefore quadruple-barreled (i.e., asks four questions at once) since it asks about the informing actions of four different individuals (Dillman et al., 2014). This question writing gaffe results in problems for researchers using the collected data. For instance, researchers are unable to explore which group of informants was particularly likely to tell parents about the challenges faced by their children. Such information allows researchers to get a better idea about the potential credibility of condition identification.

Another problem with this battery was conceptual overlap between the conditions provided to parents. This overlap stemmed from the inclusion of the item asking about developmental delays that affect students' ability to learn, typically used as an umbrella term. According to the CDC's National Center on Birth Defects and Developmental Disabilities (n.d.), Attention-Deficit/Hyperactivity Disorder, Autism Spectrum Disorder, hearing loss, intellectual disability, muscular dystrophy, and vision impairment are all forms of developmental disabilities/delays. Suppose a parent responding to these questions had been told that their child had a developmental delay, specifically an intellectual disability. When responding to the survey, the parent might answer "Yes" when asked about "any developmental delay" and quickly answer "No" to the rest of the items in the battery, not considering that categories may overlap. Responding in this manner would be a form of satisficing, meaning that respondents would take shortcuts to proceed quickly instead of carefully listening to and considering the remaining questions

(Groves, Fowler, Couper, Lepkowski, Singer, & Tourangeau, 2009). As a result, the validity of developmental delay responses and the subsequent measures of conditions falling under this term are called into question.

Questions about Difficulty

Table 2 contains the question text for the degree of difficulty battery presented to parents following the dichotomous disability battery. The battery tapped into the activity and participation elements of the ICF model in Figure 1 but excluded body limitations. Parents were asked to respond on a three-point scale: “No Difficulty,” “A Little Difficulty,” or “A Lot of Difficulty.” By asking parents to respond using a scale of difficulty, a broader view of the spectrum of ability was captured. Unlike the first set of disability questions, these items did not solely follow a medical model approach; instead, they more closely aligned with the bio-psycho-social model. In the question stem itself, parents were asked to compare their children to other ninth graders in a way that was reminiscent of drawing comparisons to a “typical” student. The five included items utilized functional definitions of disability; yet, the functions listed did not appear to be from any particular source. Parents reporting their children’s difficulty was demanding because they likely did not have complete information, making them ill-equipped to serve as proxies. Instead, parents possibly relied on what their children shared with them, what teachers divulged about classroom behavior and performance, or assumptions that they held about their children.

Comparative Analyses

Comparing measures from the two batteries demonstrated that asking about degree of difficulty captured more individuals experiencing potential limitations than just

asking about explicit conditions. The most straightforward comparison across the two sets was between students with a Specific Learning Disability and the question about how much difficulty the student had learning, understanding, or paying attention. For students identified as having a Specific Learning Disability (n = 1,550), 22 percent had no difficulty learning, 51 percent had a little difficulty learning, and 26 percent had a lot of difficulty learning. Comparatively, for students not identified as having a Specific Learning Disability (n = 13,740), 76 percent had no difficulty, 20 percent had little difficulty, and 4 percent had a lot of difficulty.

Parents were asked whether their children received special education services during the base-year and the first follow-up, with a prompt telling them that students who receive these services often have IEPs. During the first follow-up, 73 percent of parents who reported that their children received special education services during the base-year stated that their children were still receiving those services. Table 3 contains results of several crosstabulations between specific conditions and whether or not the student received special education services during the base year. Overall, the pattern trended with which types of disabilities would lead to a school offering special education services; however, more highly skewed results were expected. For instance, one would expect a larger proportion of students with autism to receive special education services and a smaller proportion of students with bone, joint, or muscle problems to receive services. This expectation is rooted in the types of services offered to assist students with disabilities in the process of learning – a wider array of services is available for some disability types than others.

The final disability-related measure from the parent instrument asked if the student was taking medication for ADHD. A comparison between this measure and whether the student had ADD or ADHD showed that only 4 percent of students who were taking ADHD medication had not been identified as having ADD or ADHD. This small percentage suggests that parent reporting around this condition is reliable. For students identified as having ADD or ADHD, 49 percent were reported as taking medication for this form of disability.

Troublesome Amount of Missing Data

A significant concern with these parental measures of disability was the rate of missing data. During the base-year of data collection, 5,430 parents refused to respond at all (i.e., unit nonresponse). Additionally, across both of the disability batteries, close to 1,300 parents failed to provide a response (i.e., item nonresponse) to questions about particular conditions their children possessed or the degree of difficulty experienced engaging in several activities. These two sources of missing data accounted for roughly 30 percent of responses. Comparing the distribution of responses to the parental question regarding specific learning disabilities (i.e., unit nonresponse, item nonresponse, yes, no) to how urban or rural students' schools were, a measure with complete data, the distribution was very close across response options. This variable was one of several geographic measures which had complete data. Unfortunately, other variables which would have provided useful insight into who did not respond, and potentially provide an indication of bias, such as socioeconomic status were missing data as well.

Table 3. Parental Report of Specific Conditions by Receipt of Special Education Services

Reported Condition	Received Special Education Services			
	n	No	Yes	Don't Know
ADD or ADHD	1,640	63%	36%	1%
Specific Learning Disability	1,550	38%	60%	2%
Any developmental delay	760	37%	61%	2%
Bone, joint, muscle problems	450	76%	23%	1%
Hearing or vision problems	450	75%	24%	1%
Autism	190	26%	72%	2%
Intellectual disability	120	15%	83%	2%

Note. Estimates weighted using W1STUDENT weight.

Administrative Data

Two final items were used for the purpose of disability identification in this dataset, both found in the base-year student survey. Neither of these items was directly asked of students; instead, administrators were asked to provide data which was then matched to the students. The first measure, X1IEPFLAG, served as a binary indicator of whether or not the student had an IEP. Table 4 contains a comparison of this indicator with each condition type from the parent survey. Quickly, the problem of missing data became apparent. For students identified as having a Specific Learning Disability, there were 320 without administrative data regarding having an IEP. Those with hearing or vision problems or bone, joint, or muscle problems saw their sample sizes reduced to nearly half. Investigation of this problem in the dataset revealed that hundreds of schools did not provide this information to the NCES.

Table 4. Parental Report of Specific Conditions by Receipt of IEP

Reported Condition	Had Individualized Education Program			
	n	No	Yes	Missing
Specific Learning Disability	1,230	17%	83%	320
ADD or ADHD	1,040	36%	64%	600
Any developmental delay	600	16%	84%	160
Bone, joint, muscle problems	210	52%	48%	240
Hearing or vision problems	240	50%	50%	210
Autism	170	7%	93%	20
Intellectual disability	120	7%	93%	0

Note. Estimates weighted using W1STUDENT weight.

The second item included in the student survey data was an indicator of whether or not the student received accommodations on the mathematics assessment administered by the NCES as part of the data collection. Accommodations were either stipulated in a student’s IEP or by school officials during the time of the administration. This measure was captured during the base-year and the first follow-up, but I only discuss the base-year indicator here because the rest of the disability measures were captured during this same time. Ninety percent of students who received an accommodation on the assessment also had an IEP. Assuming that the remaining 10 percent of students who received an accommodation were those who school officials indicated needed accommodations during the assessment was reasonable.

How Valid were these Data?

As stated previously, when considering how valid the disability-related data in HSL:09 were, I focused on content, response process, and relations to other variables. These data left much to be desired in the realm of content. The types of conditions and difficulty experienced included in the survey did not seem to be derived from any established source of authority on disability. In the list of conditions, the covered conditions even overlapped with one another conceptually. When considering the

response process, the goal is for all respondents to share a similar understanding of what is being asked by each question. This goal was not met with the NCES questions. Conceptual overlap of conditions likely led to confusion and misreporting because parents were unsure if they should respond affirmatively to multiple items for a single type of impairment. Additionally, the condition and difficulty questions asked multiple questions at once, leading to the interpretation of a “Yes” or “A lot of difficulty” not being consistent across respondents. Finally, variables were compared to one another, providing some validity support for the items. Crosstabulations produced patterns that were similar to expected distribution of responses; however, measures were not as strongly related as was expected, most notable in Table 3. Altogether, the disability-related measures included in the HSLs:09 lacked validity across multiple focal areas. Descriptive comparisons demonstrated the only validity support for the items, suggesting the need to revise these measures for future research endeavors.

Discussion and Implications

The above evaluation of definitions and resulting measures found in the HSLs:09 offers an interesting platform for considering the needs of researchers studying disability in educational contexts. These results have important implications for revisions of the HSLs:09 in particular; however, concepts apply broadly to data collection efforts. Narrow examples from the HSLs:09 instrument and data are subsequently used to highlight adjustments that are needed across education-based survey instruments in general.

Move Away from the Medical Model

As stated previously, disability is a fluid identity, likely to change as students proceed through the educational system (Bittinger & Acquino, 2017). Changes in identification may arise from a number of scenarios such as a physical injury resulting in paralysis, being presented with class material in newly inaccessible ways, or deciding to withhold disclosing their identity to avoid social stigma (Litner, Mann-Feder, & Guerard, 2005). Despite this fluidity, disability identity-related measures were only captured during the base-year of data collection, failing to take into account changes in impairment and the environment (de Leon & Freedman, 2015). Students whose diagnoses or disability-related identities changed during later years of high school were not identified in the dataset.

Measuring disability as a static identity reflects a medical model approach to disability. Moving forward, longitudinal education studies must allow disability identity to fluctuate. The first step toward this end involves asking respondents about their disability identification during each wave of data collection. Doing so provides researchers with a more accurate picture of the shifting nature of disability and allows them to study important outcomes that could be influenced by changes in identification of disability. Researchers have an ethical obligation to respect participants taking part in their research. Approaching disability measurement from a social or a bio-psycho-social model allows for the demonstration of respect for students with disabilities. Allowing these students to self-identify as experiencing a range of limitations is more empowering than asking if they fit into a diagnosis or “condition” box.

Avoid Conceptual Overlap

The inclusion of a developmental delay response option was problematic because it created a situation where response choices overlapped conceptually. Following the definition from the CDC's disability-focused center, developmental delay is an umbrella term for numerous types of disabilities, several of which were subsequently asked about separately on the survey instrument. This led to potential measurement error by way of satisfaction by parental proxies (Groves et al., 2009). For researchers, this calls into question whether the included developmental disability types were accurate on their own.

With this accuracy in question, those hoping to use these data to disaggregate results across disability types must plan ahead. A possible solution, especially in light of small sample sizes across a few categories, is to combine several measures into a new developmental disability category. However, combination would result in researchers losing the ability to consider outcomes for the populations separately and may lead to problematic interpretations. Survey designers must strategize about ways to avoid conceptual overlap when asking about disability. An apparent option is to model the disability categories included on surveys after pre-existing lists, such as the thirteen included in the IDEA. Following this list in particular is desirable because the list was created with education in mind, while other lists may only include education as one of many considerations.

Allow Self-Identification of Disability

Parents acted as proxies for disability-related questions on the HSLs:09. To some extent, this made sense. These students were minors at the time, and their parents likely accompanied them to see licensed professionals to get assessed for any of the conditions

listed on the survey. Using parents to capture this information also served as a nice way to mitigate social desirability bias around disability perceptions. Students might have been less likely to report “having” any of the listed conditions. However, as mentioned above, disability self-identification can be quite useful for researchers and empowering for respondents. Self-identification should be the gold standard to aim for when designing survey questions to measure disability identity. If survey designers wish to retain parental proxy reporting, they should also add self-identification questions to student surveys. When both parents and students respond to questions pertaining to disability identity, responses can be compared to investigate congruence or discrepancy between the two sources. Educational outcomes (e.g., college enrollment, persistence) for students whose identities do not align with parental reports can be examined to determine if potential unidentification impacts these students negatively along their educational journeys.

The second battery of disability items asked parents to rate the degree of difficulty experienced by their children at school across several activities. Parents were ill-equipped to respond to these questions and forced to rely on information that children may or may not have shared with them or any information shared with them from teachers or other school officials. Relying on teacher reports about students results in a twice-removed proxy response - not an ideal situation. If parents did not have any of this information, they likely made assumptions about their children’s experiences in order to answer the questions which introduced measurement error into the data.

This battery dealt with perceived difficulty, and perceptions are rarely pre-formed by respondents (Groves et al., 2009). Whereas something factual (e.g., Do you have a bathroom at home?) is readily available and shared with others (in this case, parents),

perceptions are formed when respondents are asked a question. Therefore, an argument for using proxies (they are more or equally as informed of the information as the intended respondent) was not satisfied. These degree of difficulty questions should be moved to the student questionnaire in future iterations of the NCES' secondary longitudinal studies. Designers of survey instruments planning to utilize proxies must carefully consider if those individuals are fully equipped to accurately respond. When asking about people's functional limitations across various contexts, proxies are not the optimal means to collect data.

Ask One Question at a Time

Nearly every question in the HSLs:09 intended to capture information about disability asked multiple questions at once. The initial battery asking about conditions contained questions that were quadruple-barreled, while the degree of difficulty questions ranged from being double- up to triple-barreled. Condition-related questions included four informants total, two of which were likely not properly trained to identify or diagnose any of the conditions listed. Revising these questions to ask about each informant separately would introduce additional burden on respondents, which is undesirable (Dillman et al., 2014). Instead, a balance must be reached where the resulting data can be confidently assumed to represent a single concept. For HSLs:09 in particular, eliminating teachers and school officials entirely seems the most appropriate approach for the condition question. The question could then be rephrased to ask about "a doctor or other health care provider," signaling that a doctor is a type of provider. The degree of difficulty questions should be broken apart to reflect singular concepts, such as asking

about how difficult learning while at school in one question and asking about how much difficulty they experience with paying attention in class in another question.

Asking a single question at a time is a standard best practice in survey-based research (Dillman et al., 2014). For researchers, questions asking about a single concept are easier to interpret when sharing results. Single concept questions also add to the validity of an instrument because one can more readily assume that respondents had similar interpretations of the question. Response burden can also be lessened due to less cognitively demanding questions. Asking about multiple concepts at once requires respondents to consider all scenarios at once and decide how to respond if only one of multiple concepts is true or applicable to them.

Prioritize Collecting Complete Disability Data

Missing data was a recurring concern throughout this analysis. Close to 40 percent of data pertaining to disability on the parent survey was missing. The majority of this missingness was due to parental refusal to complete the questionnaire; yet, there was still a sizeable portion of parents who chose not to respond to individual disability-related questions. Disability researchers conducting complete case analyses lose nearly half of their analytic sample immediately. The loss of sample size, particularly as other variables are included in advanced statistical models, may limit the amount of power that researchers have to detect significant effects. Researchers employing multiple imputation face the decision of whether to impute all of the missing data, only that which is due to unit nonresponse, or only that which is due to item nonresponse. They must also decide whether to bring in any relevant measures from the parent survey to be used in the prediction model(s).

The NCES engaged in an incentive experiment during administration to help boost parent response rates, which did lead to capturing many more parent responses. The missing data noted above is what remained following the experiment. With the sizeable amount of missing data, whether or not parents can serve as reliable proxies for important information (i.e., disability identification) was called into question, especially since a common rationale for proxy use is to reduce rates of nonresponse (Todorov & Kirchner, 2000). Ultimately, survey researchers are urged to refrain from using parents as proxies for measuring student disability identity; however, if parent proxies are used, additional effort should be devoted to following up with nonrespondents. One approach researchers could utilize would be reaching out to nonrespondents with a version of the survey that only contains the disability-related items in order to capture this important social identity data.

Include Additional Measures

Thus far, included items have been assessed and critiqued, but there are several missing measures from this study. While administrative data were collected around whether students had IEPs, nothing was recorded identifying whether or not a student received a Section 504 plan. These plans apply to students who have trouble accessing educational material or need environmental modifications but do not require special education services. An estimated 1.2 percent of students are covered by only Section 504 (Holler & Zirkel, 2008), and many more receive these plans in addition to IEPs. These plans often cover students with disabilities who do not qualify for IEPs and having this information would serve to more holistically consider institutional supports provided to students.

Only a single measure on the HSLS:09 began to tap into mental health concerns. This item asked about the amount of difficulty students experienced with depression or anxiety, two separate concepts. With the increased amount of attention being placed on college student mental health, including appropriate measures to better understand any mental health concerns students experience in high school would prove fruitful. Survey designers should include measures dealing with mental health throughout students' educational journeys. These data would shed some additional light on the fluctuations in mental health as students transition to higher levels of education.

Conclusion

While the measures included in the HSLS:09 have room for improvement, they are some of the most up-to-date nationally generalizable data available to researchers studying the transition from high school to college for individuals with disabilities. The NCES is moving in the correct direction by including questions to capture both binary condition identification and the spectrum of difficulties students face. Continuing to move in this direction will align more closely with the ICF model which is widely used globally when conceptualizing disability. Disability researchers and survey methodologists should convene to create an adapted version of the ICF model which more closely considers educational matters. Movement to align with this model is integral so that disability researchers around the globe are able to share approaches and results more readily. Researchers working with the HSLS:09 data currently are best served to follow the advice of critical quantitative researchers (e.g., Vaccaro et al., 2015). Doing so will guide them in developing questions that are appropriate and answerable

with the existing data. Taking a critical quantitative lens can also help to identify ways to group disability types, when necessary, without perpetuating a cycle of marginalization.

CHAPTER 3

INFLUENCE OF STEM VALUATION AND SUCCESS EXPECTATIONS ON MAJOR DECLARATION FOR STUDENTS WITH DISABILITIES

While students with disabilities are enrolling in postsecondary education in greater numbers (Snyder, de Brey, & Dillow, 2016), their likelihood of college enrollment is still only a fraction of the likelihood of their peers without disabilities (Wagner, Newman, Cameto, Garza, & Levine, 2005; Young & Browning, 2005). Along with the lower postsecondary participation rates, persons with disabilities have been identified as an underrepresented population within science, technology, engineering, and math (STEM) fields (National Science Foundation, 2015). Part of the postsecondary participation discrepancy can be explained by the large number of students with disabilities who do not graduate from high school. For instance, students with learning disabilities are two to three times more likely to drop out of high school than students without learning disabilities (U.S. General Accounting Office, 2003; Young & Browning, 2005). The lower secondary and postsecondary completion rates impact the employability of this population, hampering opportunities for upward social mobility.

The number of jobs requiring some form of postsecondary education continues to rise (Carnevale, Smith, & Strohl, 2010), and bachelor's degree recipients, on average, earn 84 percent more over the course of their lifetimes than individuals who only receive high school diplomas (Carnevale, Rose, & Cheah, 2011). In light of the critical role of postsecondary credentials, employment outcomes for persons with disabilities stand to be improved. The unemployment rate for these individuals is twice as high as persons

without disabilities (Bureau of Labor Statistics, 2017) and they have lower median monthly incomes (Brault, 2012). Underrepresentation in postsecondary education in general and STEM education in particular must be overcome to help boost employment potentials.

This chapter explored the relationship of the beliefs students held in regard to their ability to succeed in STEM classes, guided by Eccles and colleagues' (1983) expectancy-value framework with students' intentions to declare STEM majors upon college enrollment. This framework has been applied to many populations and topics, including STEM, serving as the basis for group comparisons, namely in regard to gender and race (e.g., Andersen & Ward, 2014; Eccles, 2011). Much like the limited research on STEM underrepresentation overall, these comparisons have thus far not included disability status. The purpose of this chapter was to identify the elements of the expectancy-value framework that were most influential on students' STEM major declaration behavior. Results begin to address the gap in the literature that is all too common for this under-researched population (Peña, 2014; Kimball, Wells, Ostiguy, Manly, & Lauterbach, 2016) and identify potential strategies for encouraging additional students with disabilities to pursue STEM-related majors. If educators help to increase representation in STEM for those with disabilities, the resulting graduates will be ready to pursue the growing number of well-paying careers in STEM (Bureau of Labor Statistics, 2009). Greater pursuit of these career opportunities could help address the growing need for individuals in these fields as well as better the employment-related outcomes for individuals with disabilities.

Frameworks

Expectancy-Value Model

The expectancy-value model of achievement motivation suggested that an individual's choice and performance in an activity can be explained by the beliefs they hold regarding their task-specific ability and the value that they place on a task (Wigfield, 1994; Wigfield & Eccles, 1992). When initially proposed, this model was tested against high school math achievement but has since been extended to other academic outcomes such as graduation and persistence. Within the subjective task value portion of the model, four constructs were included: a) attainment value, b) intrinsic value, c) utility value, and d) cost.

Attainment value was conceptualized as representing the relative importance individuals place on doing well in specific tasks (Wigfield & Eccles, 2000). Intrinsic value represented the pleasure individuals receive from engaging in a task. Utility value related to the usefulness of a given task in relation to individuals' future plans and/or goals. Finally, cost encompassed several dimensions: emotional costs, anticipated amount of effort required to engage in the activity, and opportunity costs. The expectations for success concept represented how successful individuals believe they will be if they engage in the proposed task. In education research, this concept is typically represented by subject-specific (e.g., math, science) measures of self-efficacy.

Identity Development

Interacting with and influencing change in a person's expectations for success and value placed on activities is their identity development. Relating to the expectancy-value model, two manifestations of identity are important to consider: personal and social

(Eccles, 2009). An individual's personal identity represents how they perceive themselves, including ideas around skills possessed, goals set, and values held closest. Meanwhile, social identities encompass how one relates to society through association with social groupings (e.g., gender, race, disability). Context plays a vital role in the expression of these forms of identity; as a person moves from one setting to another, different aspects of their identity become more salient. For students with disabilities, they may only experience impairment in certain situations. As an example, a student using a wheelchair may be able to get around school without problems but may have difficulty participating in lab activities where high tables are used.

Identity plays an important role in the altering of subjective task values across gender expressions and racial and ethnic groups (Eccles, 2009; Simpkins & David-Kean, 2005). Alterations result from external influences such as cultural effects and socialization processes impacting identity development. Students may come from cultures which place differential weight on certain types of knowledge or professions, influencing the types of careers to which they aspire. As children grow up, they are exposed to a number of forms of socialization that influence their interests and the values that they will place on different subjects in school. Socialization may occur through the toys children play with, the shows they watch, or whether parents and teachers encourage studying particular subjects.

While the relationship between identity development and the expectancy-value model has been explicitly identified among gender and racial identities, similar processes are likely occurring across disability identities. Students with disabilities may be socialized by teachers to believe they are less capable of engaging in rigorous math or

science classes in high school (Alston & Hampton, 2000). Such socialization may lead students to place less intrinsic value on math or science. Decreases in intrinsic value leads to less engagement with the subject(s) and less attainment value (Eccles, 2009). When students place lower values on these subjects, they may no longer see related career paths as viable. In the career choice literature, this process is known as circumscription and compromise (Gottfredson, 1981; 1996). As students enter high school, their socialization experiences lead to circumscription of career options that are not acceptable. From the remaining career options, compromise entails the selection of the most accessible options that remain. In this way, the declaration of career aspirations, and by extension college major selection, is driven by students' personal and social identities.

Literature Review

STEM Education and Declaring a College Major

The path to eventual graduation with a STEM-related degree is commonly depicted as a leaky pipeline. Following this pipeline metaphor, water flows from a large pipe to successively smaller pipes and there are leaks at each pipe transition. In this metaphor, the water represents the quantity of students on track to earn a STEM degree; leaks represent the loss of students to other majors and students dropping out of higher education altogether. At its largest part, this pipeline contains all ninth-grade students, suggesting that by default all students enter the STEM pipeline once they enter high school. Even at this early stage of high school, students' creation of STEM-related career plans is predictive of their eventual attainment of degrees in related fields (Maltese & Tai, 2011; Syed, Azmitia, & Cooper, 2011; Tai, Liu, Maltese, & Fan, 2006).

Taking the proper classes is an important influence on eventual postsecondary plans, as are students' levels of interest in various subjects. When high school students completed rigorous curricula, their chances of completing college increased (Adelman, 2006; Trusty, 2002; Tyson, Lee, Borman, & Hanson, 2007). Students who showed interest in STEM fields as early as eighth-grade were likely to continue on to earn STEM degrees (Tai et al., 2006). Interest was a powerful predictor of subject area persistence even when academic achievement and socioeconomic status were included in analyses (Simpkins, Davis-Kean, & Eccles, 2006). Additionally, early high school perceptions of the utility of science were stronger predictors of eventual STEM degree completion than science achievement scores (Maltese & Tai, 2011). Taken together, this research suggests that high school students who value math and/or science are likely to continue studying these subjects, remaining in the STEM pipeline, despite their academic performance in related classes.

For students with aspirations related to STEM fields, completing the proper classes while in high school is critical. Completion of these classes prevents students from having to catch up through mechanisms such as remedial education or taking additional lower level courses before beginning college-level STEM courses. Without these classes in high school, students are not poised to successfully enter STEM majors in college (Lynch, 2011) and are at risk of leaking out of the STEM pipeline (Lee & Luykx, 2006). When students fall out of the STEM pipeline, they rarely re-enter (Maltese & Tai, 2011). Therefore, additional efforts to retain students are needed, especially when students demonstrate high levels of interest or see STEM as particularly useful.

While the values that students place on math and science in high school are helpful in predicting who will be retained within the pipeline, expectations for success also play an important role in understanding who decides to persist (Andersen & Ward, 2014). In a study following STEM-aspiring students beginning in eighth grade, mathematics self-efficacy and proficiency were predictive of who ultimately persisted in their career plans (Mau, 2003). An additional barrier to pursuing STEM is overcoming the culture of the subject-specific fields which may conflict with students' identities. The stereotypical cultures of some STEM fields, such as science, prevent students from being able to incorporate math and science into their identities (Archer, Hollingworth, & Halsall, 2007; Taconis & Kessels, 2009). Science fields are commonly seen as being occupied by able-bodied White men, creating dissonance within the social identities of women, racial minorities, and persons with disabilities. Further, science disciplines tend to be individualistic and competitive, clashing with the preferred learning styles of minority students (Heilbronner, 2011). With this conflicting culture in mind, the underrepresentation of women, racial minorities, and individuals with disabilities is understandable.

Underrepresented Populations in STEM

A considerable amount of work has been done on two of the three NSF-identified (2015) underrepresented populations in STEM: women and racial minorities. While neither population was the focus of this chapter, I briefly review related findings because the exclusionary experiences of these two groups was informative for considering reasons why students with disabilities may leak out of the STEM pipeline. Black students' math and science class choices were influenced by the intrinsic and utility values they placed

on each subject (Lewis & Connell, 2005). As the value these students placed on science and math eroded, they were disinclined to complete additional STEM classes in high school to prepare them to pursue related majors in college. Similar results arose from gender-based research, demonstrating that women were, on average, less interested in STEM careers leading to less value placed on obtaining related credentials (Eccles, 2005).

As mentioned previously, the culture of STEM fields is often incongruent with an individual's identity. When this occurs, students must decide whether to retain their personal and collective identities or give these up for the sake of joining the ranks and adopting the culture of those already in these fields. For racial minority students, such situations may make them feel as though they must assimilate in order to succeed, forfeiting their racial identities (Cooper, 2011). A lack of minority role models within STEM disciplines led to the belief that careers in these fields were out of reach and unreasonable to aspire (Archer et al., 2007). Without same-race role models, racial minority students believed that they were unlikely to be successful pursuing majors or careers in STEM (Hines, 2003), leading to them placing lower valuations on these subjects during high school.

Expectations that women and racial minorities have for success in STEM also shape their desires to major in and ultimate persistence in associated majors. Women who viewed themselves as having high ability in math were likely to declare desires to pursue STEM-related careers (Eccles & Wang, 2016). Further, family values, a component of a person's identity, were influential in determining whether women sought STEM careers. A study of Mexican American middle-school students found that mathematics and

science self-efficacy were related to students' academic and career goals (Navarro, Flores, & Worthington, 2007). An earlier study found similar support for students of low socioeconomic backgrounds residing in inner-cities (Fouad & Smith, 1996). Goal persistence for students with disabilities from underrepresented racial identity backgrounds were also influenced by self-efficacy beliefs (Cardoso, Dutta, Chiu, Johnson, Kundu, & Chan, 2013).

Students with Disabilities Pursuing STEM

Students with disabilities enter high school with aspirations of pursuing higher education at rates similar to their peers without disabilities; however, their aspirations are considerably lower by graduation (Hitchings, Retish, & Horvath, 2005). Their lessened aspirations correspond to the lower proportion of students with disabilities in higher education, on average (Snyder et al., 2016; Wagner et al., 2005), which is further complicated by the higher likelihood of dropping out of high school amongst members of this population (Young & Browning, 2005). In terms of STEM education, one study indicated that students with disabilities continuing into postsecondary education had similar likelihoods as those without disabilities to initially declare STEM-related majors (Lee, 2011). Despite the initial interest in majoring in a STEM discipline, students with disabilities are underrepresented among eventual degree recipients in these fields (NSF, 2015). However, additional research is needed to replicate Lee's (2011) results.

In general, students with disabilities constitute a smaller proportion of STEM degree earners than their population size would anticipate; yet, students with an autism spectrum disorder stray from this trend. Setting a goal of college enrollment during high school was positively associated with rates of college going among these students (Wei,

Wagner, Hudson, Yu, & Javitz, 2016). Compared to students with other types of disabilities, those with an autism spectrum disorder were more likely to pursue a major in STEM (Wei, Yu, Shattuck, McCracken, & Blackorby, 2013). It would seem that at least for this subpopulation, STEM fields are regarded as desirable, perhaps even more so than other major choices in postsecondary education.

From an expectancy-value perspective, high school and college students select classes partially based on how well they think they will perform in them and how closely the classes align with their identities (Andersen & Ward, 2014; Eccles, 2009). However, for students with disabilities, this view on class selection might be a bit more complicated. During high school, and the preceding school years, these students are protected under the Individuals with Disabilities Education Act (2015), guaranteeing them a free and appropriate public education in the least restrictive environment possible. Under this Act, many students with disabilities have individualized education programs (IEPs) designed for them by teams composed of parents, teachers, and administrators. While students without disabilities may have the flexibility to freely choose the classes they would like to take, the class selection for those with disabilities is influenced by the IEP team. These teams are supposed to help create plans for these students to prepare them for postsecondary outcomes (e.g., employment, living independently); however, few of these programs adequately prepare students to pursue postsecondary education (Hitchings et al., 2005).

Relatedly, students with disabilities were less likely than their peers without disabilities to complete college preparatory classes while in high school (Sparks & Lovett, 2009). These classes establish foundational knowledge students will build upon

during postsecondary education and cannot simply be avoided. Students entering higher education must decide how to complete these classes so that they can move onto more advanced classes. Approaches may include attending a community college initially or enrolling in remedial education during their first year, both of which introduce additional costs. If students with disabilities are not completing the appropriate math and science classes in high school, the enhanced cost may make pursuing a STEM major unrealistic. Without these classes, students will lack the foundational knowledge to begin the postsecondary college curriculum (Lynch, 2011) and may resultingly leak out of the STEM pipeline (Lee & Luykx, 2006).

As a whole, limited research has applied the expectancy-value model to the experiences of students with disabilities despite its promise for helping to better understand decisions pertaining to college major choice among high school students. The following analysis begins to address this gap in the education literature by applying the expectancy-value framework to students with disabilities specifically. Additionally, the framework was used to predict the likelihood of students with disabilities pursuing STEM majors once they reach college. Within the prediction model, interaction effects were tested to identify whether certain disability types moderated the relationships between demographic variables or expectancy-value on the outcome variable. The following questions guided my analysis:

1. To what extent do students with disabilities differ from students without disabilities on expectancy-value model factors?
 - a. To what extent are these differences present across disability types?

2. To what extent are the subjective task value factors (i.e., intrinsic, utility, attainment values, cost) predictive of who intends to declare a STEM major upon college enrollment for students with disabilities?
 - a. To what extent do the relationships between the subjective task value factors and STEM major declaration intentions differ by disability type?
3. To what extent are students' expectations for success predictive of who intends to declare a STEM major upon college enrollment for students with disabilities?
 - a. To what extent does the relationship between expectations for success and STEM major declaration intention differ by disability type?

Method

Data for the subsequent analysis were drawn from the HSLs:09, a longitudinal study sponsored by the National Center for Education Statistics (NCES) with a focus on high school students as they move through high school and onto postsecondary activities (Ingels et al., 2015). These data were drawn from a stratified random sample of public and private school students who were in ninth-grade in 2009. In the present chapter, predictor variables were captured during the base-year of data collection and the outcome variable, intention to declare a STEM major upon enrollment, came from the 2013 update. Predictor variables came from both the student and parent surveys.

Sample

In total, approximately 24,000 students participated in the base-year of data collection (Ingels et al., 2015). Of particular importance to this study was the subsample of students with disabilities. During the base-year of data collection, students were not asked to self-identify as having a disability; instead, parents were asked whether they had

been informed that their children had any of the following conditions by a doctor or school official: learning disability, developmental delay, autism, hearing/vision problem, bone/joint/muscle problem, intellectual disability, or ADD/ADHD. From the response options provided to parents, I selected five disability categories that were incorporated into my analysis: learning disability, sensory impairment, mobility impairment, ADHD, and developmental delay. Students with autism and/or intellectual disabilities only were excluded from my analysis, resulting in a loss of 10 respondents. While retaining these students was desirable, do so would have necessitated combining multiple disability categories. This combination would have resulted in interpretations that were less clear, especially given prior research which has identified students with autism spectrum disorders as being more likely to pursue STEM subjects.

I narrowed my analytic sample in a number of ways. First, I dropped all students who were not enrolled in college during the 2013 update. My outcome of interest pertained to the type of major declared by students, and students who were not enrolled in college legitimately could not answer this question. A large number of parents did not respond to the parent survey during the base-year. Due to the fact that parents were asked about disability instead of students, no disability information was captured for a number of students. As a result, I excluded students from my analytic sample whose parents did not respond to the survey – about 20 percent of the remaining sample. Several predictor variables were only asked to students who were taking a math and/or science course, so I dropped students who were not taking a math and a science course during their 9th grade academic year. Finally, I removed students who did not respond to the base-year survey at all. All of these decisions led to a reduction in the analytic sample from around 24,000

students to 8,950 students. These 8,950 students were used to answer my first research question comparing expectancy-value model factor values between students with disabilities and those without. After this comparison, all students who were not identified as having a disability were excluded from my analytic sample, for a final sample size of 1,270. This final sample was used when answering research questions two and three.

The narrowing of my analytic sample was of concern due to my desire to include disability as five separate categories as opposed to a binary variable condensing all forms of disability into a single indicator. After the sample size reduction, the number of students with each type of disability were as follows: learning (490), sensory (200), mobility (250), ADHD (700), and developmental (230). Disability types were not mutually exclusive, and approximately 28 percent of these students experienced multiple forms of impairment. Students were allowed to belong to multiple disability identity groups to acknowledge the different challenges that students would face depending on their impairment(s). Condensing the 28 percent down into a multiple disabilities category to make all impairment categories mutually exclusive would have resulted in meaningless interpretations for the condensed category. These sample sizes were sufficient for stable regression models, particularly because the majority of my final model would be composed of aggregated scales as opposed to a large number of independent variables. When fitting logistic regression models, I checked standard error estimates as an indicator of instability to detect potential inflation due to sample size constraints.

Remaining missing data in my analytic sample were handled through multiple imputation, which utilized a fully conditional model incorporating design weights to account for the clustering of the data (Reiter, Raghunathan, & Kinney, 2006). Prior to

imputation, it was determined that if list-wise deletion was used, 72 percent of the data would be available. A total of 28 datasets were imputed, following the advice that researchers should impute as many datasets as the percentage of missing data (Bodner, 2008). Across the variables to be imputed, rates of missing data were generally low, accounting for under 5 percent of the data for most variables. The only variable with a higher rate of missing data was the outcome variable, which had approximately 13 percent missing. This percentage was largely attributable to my recoding of “Don’t Know” responses when students were asked about their intended majors. Some of these students will likely end up pursuing STEM majors during college, so instead of considering these responses to be non-STEM, I coded them as missing so that I could impute their major choice. Additionally, a relatively small number of students were not asked this question at all because they received an abbreviated interview during the 2013 update.

Subjective Task Value and Expectations for Success Variables

During question design of the HSLs:09, the Eccles et al. (1983) expectancy-value model was employed, resulting in questions representing several aspects of the model (Ingels et al., 2011). Several scales were created representing each of the four components of subjective task value as well as expectations for success. A number of these scales were formed by the NCES and included in the dataset, while others were derived from the work of Andersen and Ward (2014). When possible, scales separately represented subjective task value concepts for math and science; however, questions around cost asked students about math and science jointly. Scales were calculated prior to multiple imputation because factor analysis cannot yet be performed on multiply imputed

data in Stata. Some of the calculated scales were only represented by two measures, so confirmatory factor analysis was not possible due to lack of degrees of freedom (Kline, 2016). Instead, exploratory factor analysis was employed to ensure measures were loading onto a common factor and Cronbach's alphas were calculated to assess internal reliability. Alpha values were calculated for the sample overall and across disability types separately. Scales were then created by calculating the mean across the measures for each construct and centering the factors at zero following imputation.

Scales identified by the NCES included math and science identity, utility, and self-efficacy (Ingels et al., 2015). The questions making up all six scales asked students to respond on four-point Likert-type scales. Table 5 contains complete question text, response options, and alpha coefficients for each scale. Identity was used to represent attainment value because this aspect of subjective task value is closely tied to individuals' identities. Engaging in tasks is meaningful to individuals to the extent that doing so is consistent with their identities (Eccles, 2009). Math and science identity scales were made up of two measures each, representing whether students saw themselves as math or science people and whether others saw them as math or science people. Overall alpha values were 0.84 for both math and science identity. Across disability categories, similar alpha values were calculated, raising no cause for concern. Students with scores above zero on these scales more highly identified with these subjects, meaning they placed above average attainment value on science and/or math.

Math and science utility scales were both composed of three measures and referenced the classes students were taking at the time: a) usefulness of class for everyday life, b) usefulness of class for college, and c) usefulness of class for future

career. Overall alpha values were 0.76 for math utility and 0.74 for science utility.

Similar alpha coefficients were found across disability types. Students with scores above zero on these scales placed higher than average values on the utility of math and science.

Math and science self-efficacy scales were composed of four measures each and related to the math/science course the student was taking at the time. Questions included whether students were: a) confident that they could do an excellent job on tests, b) confident that they could do an excellent job on assignments, c) certain that they could understand the most difficult material in the textbook, and d) certain they could master the skills being taught. Overall alpha values were 0.89 for math self-efficacy and 0.88 for science self-efficacy. Similar alphas were calculated across disability categories for self-efficacy scales. Self-efficacy was used to represent students' expectations for success in math and science; scores above zero indicated that students had higher than average expectations that they would succeed in math and/or science.

Andersen and Ward (2014) identified measures used for the remaining two components of subjective task value: intrinsic value and cost. Math and science intrinsic values were represented by two questions each, which asked whether or not students planned to take additional math and/or sciences classes because they enjoyed studying or were good at either subject. These questions were measured dichotomously. Calculated alpha values for these two scales were the lowest of any of the included scales: 0.69 for math intrinsic value and 0.75 for science. Similar values were calculated for math intrinsic value across disability types, but alpha values for the science intrinsic value scale ranged from a low of 0.67 for students with learning disabilities up to 0.77 for students with sensory disabilities. For students who had scores above zero on these

scales, they placed a higher intrinsic value on math and/or science, meaning they were more interested in these subjects than average.

Finally, cost was measured through a set of questions that asked about math and science jointly. Students were asked to respond to what degree spending a lot of time and effort on their math/science classes would result in: a) not having enough time to hang out with friends, b) not being popular, c) people making fun of them, and d) not having have enough time to engage in extracurricular activities. The overall alpha value for this scale was .76; similar values were calculated across disability types. Students with scores above zero on this scale perceived the costs of pursuing science and math to be higher than average.

Table 5. Scale Question Text, Response Options, and Alpha Coefficients

Scale	Question Text	Response Options	Alpha Coefficient
Math Attainment Value	You see yourself as a mathematics person. Others see you as a mathematics person.		0.84
Science Attainment Value	You see yourself as a science person. Others see you as a science person.		0.84
Math Utility Value	Math is useful for everyday life. Math is useful for college. Math is useful for a future career	Strongly Agree, Agree,	0.76
Science Utility Value	Science is useful for everyday life. Science is useful for college. Science is useful for a future career	Disagree, Strongly Disagree	0.74
Math Expectations for Success	You are confident that you can do an excellent job on tests in this course. You are certain that you can understand the most difficult material presented in the textbook used in this course.		0.89

	<p>You are certain that you can master the skills being taught in this course.</p> <p>You are confident that you can do an excellent job on assignments in this course.</p>		
Science Expectations for Success	<p>You are confident that you can do an excellent job on tests in this course.</p> <p>You are certain that you can understand the most difficult material presented in the textbook used in this course.</p> <p>You are certain that you can master the skills being taught in this course.</p> <p>You are confident that you can do an excellent job on assignments in this course.</p>		0.88
Math Intrinsic Value	<p>What are the reasons you plan to take more math courses during high school? You are good at math.</p> <p>[...] You enjoy studying math.</p>		0.69
Science Intrinsic Value	<p>What are the reasons you plan to take more math courses during high school? You are good at science.</p> <p>[...] You enjoy studying science.</p>	Yes, No	0.75
STEM Cost	<p>If you spend a lot of time and effort in your math and science classes ... you won't have enough time for hanging out with your friends.</p> <p>[...] you won't have enough time for extracurricular activities.</p> <p>[...] you won't be popular.</p> <p>[...] people will make fun of you.</p>	Strongly Agree, Agree, Disagree, Strongly Disagree	0.76

Modeling Major Declaration Intention

My outcome of interest, students' intention of declaring a STEM-related major upon enrollment in college, was binary, so multiple logistic regression was used during

modeling (Hosmer & Lemeshow, 2000; Menard, 2002). The base model included demographic and background measures representing the five disability categories, whether or not the student was an underrepresented racial minority, gender, and a standardized mathematics assessment score. Demographic characteristics were included based on the NSF (2015) report identifying these two groups along with individuals with disabilities as underrepresented in STEM fields and careers. The students' standardized mathematics assessment scores came from the mathematics proficiency exam administered by the NCES.

I then added the expectancy-value components into the model. Variables were included in the model individually, selected based on results of Chi-squared model comparison tests (Menard, 2002). Statistically significant Chi-squared tests, at the 0.05 level, suggested that measures improved overall model fit and were thus retained even if the measure itself was not statistically significant in the model. After all components were simultaneously entered into the expectancy-value model, I tested interaction effects between the disability categories and the retained expectancy-value predictor variables in the model in order to detect moderation effects (sub-questions for research questions two and three). Interaction terms were also retained based on results of Chi-squared model comparison tests (Jaccard, 2001). Because of the continued identification of women, racial minorities, and persons with disabilities as underrepresented populations in STEM fields, interaction effects between disability types and gender and race were also tested. It was anticipated that the added presence of disability to these identity characteristics might further reduce students' likelihood of pursuing STEM majors. Model coefficients

were converted to predicted probability values by converting the log odds to odds and then odds to a probability by dividing the odds by one plus the odds.

Results

Prior to building the predictive model of intention to declare a STEM major, several proportions and means comparisons were conducted to identify descriptive differences between students with learning, sensory, mobility, ADHD, and developmental delays as well students with no type of disability in terms of the calculated scales representing expectancy-value model factors. Table 6 contains the calculated differences from these comparisons. Because the disability categories were not mutually exclusive, comparisons were conducted for each disability category separately. For each difference in Table 6, the number represents how the column group compared to their reference group. Each column group's reference group was the opposite group (e.g., students with learning disabilities compared to students without learning disabilities, students with no disability compared to students with any disability). For example, the calculated difference for math attainment value for students with learning disabilities was -0.18. This meant that, on average, students with learning disabilities had math attainment values 0.18 units lower than students without learning disabilities. Also for math attainment value, students with no disability (labeled "None"), had a difference of 0.15. This meant that, on average, students with no disability rated their math attainment value 0.15 units higher than students with any disabilities. The final column in Table 6 is therefore similar to the comparisons of students with and without disabilities in other research that includes disability as a binary characteristic of interest.

Table 6. Descriptive Comparison Differences across Disability Types^a

	Disability Categories					
	Learning	Sensory	Mobility	ADHD	Developmental	None
STEM Major	-0.06*	0.00	-0.03	0.04	-0.02	0.01
Woman	-0.14**	-0.14**	0.09	-0.25**	-0.16**	0.15**
Under-represented Racial Minority	-0.02	-0.03	0.04	-0.07**	0.02	0.05
Math Proficiency	-7.43**	-1.14	-0.48	-3.54**	-7.31**	3.79**
Math Attainment Value	-0.18**	-0.12	0.06	-0.17**	-0.31**	0.15**
Science Attainment Value	-0.11	-0.11	-0.11	-0.01	-0.22**	0.09*
Math Utility Value	0.08	0.04	-0.07	0.07	0.07	-0.03
Science Utility Value	-0.02	-0.04	-0.08	-0.02	-0.07	0.03
Math Expectations for Success	-0.13**	-0.02	-0.07	-0.07	-0.15*	0.10**
Science Expectations for Success	-0.16**	-0.04	-0.05	-0.06	-0.18**	0.09**
STEM Cost	0.10*	-0.07	0.12	0.10**	0.13	-0.07*
Math Intrinsic Value	-0.04	-0.02	0.06	-0.05*	-0.10*	0.04*
Science Intrinsic Value	-0.05	0.01	-0.02	-0.01	-0.05	0.02

Notes. n = 8,950; imputations = 28; weight = W1STUDENT; * p < 0.05, ** p < 0.01; All continuous variables and scales standardized to a mean of zero. ^a reference groups are the opposite (e.g., the reference group for students with learning disabilities is students without learning disabilities)

Demographic Comparisons

A few statistically significant demographic differences were detected. Students with learning (p < 0.01), sensory (p < 0.01), ADHD (p < 0.01), and developmental

disabilities ($p < 0.01$) were more likely to be men. Overall, students with no disabilities were more likely to be women ($p < 0.01$). Students with ADHD were less likely to be from underrepresented racial minority identities ($p < 0.01$). On average, students with no disabilities scored higher on the mathematics proficiency exam administered by the NCES than students with at least one type of disability ($p < 0.01$). Specific identity groups that scored lower included: learning ($p < 0.01$), ADHD ($p < 0.01$), and developmental disabilities ($p < 0.01$). Only students with learning disabilities reported intentions to major in a STEM field that were significantly lower than students without a learning disability ($p < 0.05$).

Expectancy-Value Factor Comparisons

Statistically significant differences were also detected across disability identities for the calculated scales representing subjective task value and expectations for success. Students with learning ($p < 0.01$), ADHD ($p < 0.01$), and/or developmental disabilities ($p < 0.01$) had lower average math attainment scores. Overall, students with no disabilities, on average, had higher math attainment scores ($p < 0.01$). Those with a developmental disability had lower average science attainment values than students who did not have this type of disability ($p < 0.01$). The students without any disabilities had higher average science attainment value scores than students with any type of disability ($p < 0.05$). No statistically significant differences were found for any disability type for the math and science utility value scales.

In general, students with no forms of disability had higher math ($p < 0.01$) and science expectations for success ($p < 0.01$) scores. Those with learning ($p < 0.01$) and/or developmental disabilities ($p < 0.05$) had lower math expectations for success scores than

those without each of the disability types. Students with learning ($p < 0.01$) and/or developmental disabilities ($p < 0.01$) had significantly lower science expectations for success scores. Students without any types of disability perceived the non-financial cost of taking additional STEM courses to be lower than students with at least one type of disability ($p < 0.01$). Those with learning disabilities ($p < 0.05$) and/or ADHD ($p < 0.01$) had significantly higher cost perceptions on average than students without these types of disabilities. Overall, students without any type of disability had higher math intrinsic value scores ($p < 0.05$) than students with at least one type of disability. Students identified as having ADHD had lower average math intrinsic value scores than students without ADHD ($p < 0.05$); the same was true for students with a developmental disability ($p < 0.05$). No statistically significant differences were observed across science intrinsic value scores.

Predicting STEM Majoring for Students with Disabilities

After reducing the analytic sample to include only students identified as having at least one type of disability, a logistic regression model was built to predict students' intentions of declaring a STEM major upon enrollment in college. First, a base model which included only background characteristics was run (see Table 7). Two characteristics were statistically significant: gender ($p < 0.01$) and math proficiency scores ($p < 0.01$). Women had a very low odds ratio, suggesting their likelihood of pursuing STEM majors was considerably lower than men's likelihood. Increases in math proficiency score were associated with increased likelihoods of intending to pursue STEM.

Table 7. STEM Major Declaration Intention Model with Background Characteristics, Odds Ratios

Measure	Odds Ratio	Standard Error	t
Learning Disability	0.96	0.26	-0.16
Sensory Impairment	1.37	0.43	1.00
Mobility Impairment	1.64	0.56	1.44
ADHD	1.65	0.44	1.87
Developmental Disorder	1.22	0.45	0.54
Woman	0.29**	0.07	-5.28
Underrepresented Racial Minority	0.96	0.25	-0.16
Math Proficiency	1.04**	0.01	3.03
Intercept	0.35	0.11	-3.41

Notes. n = 1,270; imputations = 28; weight = W1STUDENT; * p < 0.05, ** p < 0.01; F(8, 219.0)

Following the initial background characteristics-only model, expectancy-values were included individually. The first included measure, resulting in the greatest increase in model fit as assessed by the Chi-squared test, was math attainment value. The second, and final, included measure was science intrinsic value. After this value, no other expectancy-value model variable significantly increased model fit. Results from the addition of these two variables are shown in Table 8. Being a woman was still associated with a significantly lower odds ratio ($p < 0.01$). With the addition of math attainment value, math proficiency score was no longer a statistically significant predictor; however, math attainment value was a significant predictor ($p < 0.01$). Above average math attainment values were associated with higher odds ratios of intending to declare a STEM major upon college enrollment. While science intrinsic value significantly increased model fit, it was not a statistically significant predictor.

Table 8. STEM Major Declaration Intention Model with Background Characteristics and Expectancy-Values, Odds Ratios

Measure	Odds Ratio	Standard Error	t
Learning Disability	0.85	0.24	-0.55
Sensory Impairment	1.36	0.43	0.98
Mobility Impairment	1.51	0.53	1.17
ADHD	1.64	0.44	1.82
Developmental Disorder	1.23	0.44	0.58
Woman	0.30**	0.07	-5.00
Underrepresented Racial Minority	0.88	0.24	-0.47
Math Proficiency	1.02	0.01	1.22
Math Attainment	1.64**	0.23	3.51
Science Intrinsic	1.60	0.41	1.84
Intercept	0.35	0.11	-3.36

Notes. n = 1,270; imputations = 28; weight = W1STUDENT; * p < 0.05, ** p < 0.01; F(10, 220)

The final model introduced two interaction effects (see Table 9). As stated previously, one of the aims of this analysis was to detect any moderation effects of disability type on the relationship between measures of expectancy-value and students' STEM major declaration intentions. Interaction terms were calculated for the five included disability categories and the two expectancy-value measures included in the model. Only interaction terms that improved model fit, as assessed through Chi-squared model comparisons, were retained. This resulted in the inclusion of a single interaction term: science intrinsic value and having a mobility impairment. Additionally, interaction terms were calculated and included based on the same criteria to capture any moderation effects on disability type on being a woman or racial minority. As a result, one term was included: being a woman and having ADHD.

Table 9. STEM Major Declaration Intention Model with Background Characteristics, Expectancy-Values, and Interaction Effects, Odds Ratios

Measure	Odds Ratio	Standard Error	t
Learning Disability	0.83	0.24	-0.62
Sensory Impairment	1.35	0.42	0.96
Mobility Impairment	1.35	0.46	0.88
ADHD	2.10*	0.66	2.37
Developmental Disorder	1.27	0.46	0.65
Woman	0.49*	0.16	-2.17
Underrepresented Racial Minority	0.86	0.23	-0.56
Math Proficiency	1.02	0.01	1.18
Math Attainment	1.63**	0.23	3.47
Science Intrinsic	1.91*	0.52	2.36
Science Intrinsic x Mobility Impairment	0.40	0.27	-1.34
Woman x ADHD	0.33*	0.16	-2.25
Intercept	0.30	0.10	-3.52

Notes. n = 1,270; imputations = 28; weight= W1STUDENT; * p < 0.05, ** p < 0.01; F(12, 221.4)

To establish a baseline for comparisons, the intercept in this model is interpreted as the predicted odds when all variables in the model are equal to zero. When this is the case, the probably of a student declaring a STEM major was 23 percent. In this final model, the woman indicator variable remained significant; however, since this variable was part of an included interaction effect between being a woman and having ADHD, the odds ratio for women was considered a conditional effect (Jaccard, 2001). This variable was conditional because represented the effect of being a woman when the moderator variable (i.e., having ADHD) was equal to zero. In other words, the odds ratio depicts the odds of women without ADHD intending to declare a STEM major divided by the odds of men without ADHD intending to declare a STEM major. Holding all other variables constant (i.e., setting them equal to zero), the predicted probably of a woman intending to declare a STEM major was 13 percent. This value was roughly half of the probability of students declaring a STEM major when all predictors were equal to zero.

For the interaction term between being a woman and having ADHD, the woman indicator variable was the focal independent variable and the ADHD indicator variable was the moderator variable (Jaccard, 2001). Referring to the two variables in this manner helps make it clear that I was interested in the moderating effect of having ADHD on the impact of gender on students' intentions to declare STEM majors. The odds ratio for this term (0.34) represented a ratio of predicted odds ratios. The first odds ratio was the predicted odds for women over the predicted odds for men for students with ADHD. The second odds ratio was the predicted odds for women over the predicted odds for men for students without ADHD. Dividing the first ratio by the second ratio resulted in the odds ratio for the interaction term. The statistical significance of this interaction term indicated that the effect of being a woman on students' intentions to declare STEM majors differed for students with and without ADHD.

The only disability type that was a statistically significant predictor in this final model was ADHD. Similar to the woman indicator variable, the ADHD variable was part of an interaction term, thus represented a conditional effect. When everything else in the model was held constant, the probability of a student with ADHD declaring a STEM major was 39 percent. This probability was 16 percentage points higher than the probability of a student declaring a STEM major when all predictors were equal to zero.

Math attainment ($p < 0.01$) and science intrinsic ($p < 0.05$) values were both significant predictors. Math attainment value was a main effect with a positive association with intention to declare a STEM major. A one-unit increase in math attainment value was associated with a 10 percentage-point increase in the probability of a student intending to declare a STEM major, when all other variables in the model were

held constant. An interaction term between science intrinsic value and having a mobility impairment was included in the model; however, the term was not statistically significant. As a result, it could not be confidently stated that there was a truly differential impact of science intrinsic value on intentions to declare a STEM major for students with and without mobility impairments. Because of the lack of statistical significance, science intrinsic value was also treated as a main effect. A one-unit increase in science intrinsic value was associated with a 13 percentage-point increase in the probability of a student intending to declare a STEM major, when all other variables in the model were held constant.

Discussion

Reliability of Expectancy-Value Factors

A goal of this chapter was to evaluate the reliability of the expectancy-value measures between students with and without disabilities as well as across disability types. This intention was driven by the lack of use of the expectancy-value framework in previous research focusing on students with disabilities. The constructs that I compared were derived from previous research focused on high-ability, racially-diverse students (Andersen & Ward, 2014) and scales identified by the data sponsor. As such, conducting factor analysis and assessing internal reliability for my sample was important. My analytic sample was not limited by academic ability, represented by mathematics proficiency in the present study, so testing the items Andersen and Ward (2014) used in their study was imperative instead of relying solely on their coefficients.

Overall, the scales identified by the NCES formed clear factors and demonstrated good internal reliability, as shown through Cronbach's alpha coefficients over .80. The

scales identified by Andersen and Ward (2014) did not fit quite as well, demonstrating lower levels of internal reliability. Alpha values for these scales did not reach .80, and two were below .70, which was not ideal. These results were not entirely unexpected. Two of the factors were formed by only two measures (math and science intrinsic value), which poses a challenge to reliably measuring any construct. While the STEM cost value was represented by four measures, when they were allowed to load onto an unlimited number of factors two distinct possible factors emerged. One factor seemed to represent a construct of time, including the measures where students identified if spending time on math/science classes resulted in not having enough time to hang out with friends or not having enough time to engage in extracurricular activities. The second factor appeared to hinge on a social cost and represented the measures where students reported to what extent spending time on math/science classes resulted in people making fun of them or not being popular. Ultimately, the measures were forced to load onto a single factor and the resulting loadings were only slightly lower than when multiple factors were allowed.

Investigation of internal reliability across the five included disability identities revealed few concerns that the scales may not be appropriately representing the intended constructs for any group of students. The one scale where concerns emerged was for science intrinsic value. Cronbach's alpha values ranged widely from a low of .67 for students with learning disabilities up to .77 for students with sensory disabilities. It is likely that this is related to the general poor performance of this factor. Two measures were likely not enough to properly represent this construct, and future applications of the expectancy-value model should strive to include additional measures. This need is difficult to meet for secondary data analysts limited to adapting what has been measured

previously to their research interests. Capturing this construct as well as others with additional measures in the future will also enable researchers to conduct factor analyses within a confirmatory factor analysis framework. The present study was unable to apply this form of factor analysis as a result of the numerous factors represented by only two factors, resulting in non-converging models.

Comparisons of Expectancy-Value Factors

Numerous differences were identified across disability types on the average scores for the expectancy-value model constructs. In the aggregate, students with at least one form of disability placed lower valuations on math attainment, science attainment, and math intrinsic values. They perceived higher nonfinancial costs associated with taking more science and math classes. They also had, on average, lower expectations for success in math and science. It is worth pointing out that, in the aggregate, students with at least one form of disability did not perceive math or science as any less useful than their peers without disabilities. This lack of statistical difference was a little surprising given the lower attainment values. While these aggregate analyses of differences were informing, analyses by disability type identified how the valuation was not lower for all forms of disability.

When looking across disability types, students with learning disabilities, ADHD, and developmental disabilities were typically the groups who placed lower valuations on math and/or science and higher cost estimations on seeking additional math/science education in high school. In particular, students with learning and/or developmental disabilities had lower average expectations for success in math and science. These findings likely stemmed from socialization and previous experiences in STEM courses.

Students who have disabilities which impact their ability to learn, concentrate, or remember information may enter high school with previous educational experiences that socialized them to believe that they were not capable of successfully participating in STEM classes. Evidence of this was seen in the lower math attainment values for students with learning and developmental disabilities and those with ADHD. The lower attainment values demonstrated that these students viewed doing well in math as less important than students without these types of disabilities. Below average attainment values may lead students to avoid enrolling in more than the required math courses, which has implications for STEM participation at-large because many advanced courses require that students complete initial math course sequences.

The conceptualization of attainment in this study was closely tied to identity, and the variables composing these factors asked whether students felt like math or science people. This was in line with Eccles' (2009) more recent theorizing about the link between the expectancy-value model and identity development. Identification may explain why fewer students with learning disabilities intended to pursue STEM-related majors upon enrollment. If sense of identity is so influential to ultimate major and career intentions, this would help explain why students with disability types that, on average, were less math proficient intended to pursue STEM at comparable rates to students without disabilities. Students with learning and developmental disabilities along with those with ADHD all had lower math proficiency scores.

In the aggregate, women were less likely to be identified by a parent as having any type of disability. Specifically, they were less likely to be identified as having learning, sensory, or developmental disabilities, as well as ADHD. As a result, gender is

important to consider when investigating disability. Gender is also very important when researching STEM education since women have been underrepresented in STEM fields for quite some time (NSF, 2015). Combining these two issues, assuming that the number of women STEM aspirants with at least one type of disability would be low seems logical. Regarding racial identity, also important when focusing on STEM education, such significant differences in proportions across disability types were not found. The only difference identified was a lower proportion of racial minority students with ADHD than Asian or White students.

Expectancy-Value Factors and STEM Major Intentions

In the final model, indicators of being a woman and having ADHD were significant predictors of intentions to declare STEM majors. Perhaps not surprising given the continued underrepresentation in STEM fields, being a woman significantly decreased a student's probability of intending to pursue STEM. It is worth pointing out that this finding held true despite the analytic sample only including students with disabilities. When all other predictors in the model were held constant, students with ADHD had an increased probability of intending to pursue STEM. This was an important finding because it potentially identifies a specific disability subpopulation to target for increased participation in STEM fields.

Only two expectancy-value factors were included in this model: math attainment and science intrinsic values. Both of these values were positively associated with intentions to declare STEM majors and increasing either value by one-unit resulted in an increase in the probability of a student intending to pursue a major in a STEM field upon college enrollment. The attainment values were represented by identity-related

constructs, so this finding emphasized the important influence of students' senses of math identity on their intended majors. This made a lot of sense. Students' career aspirations are driven by how they see themselves and what they think they will be good at (Eccles, 2009). Students whose identities incorporate higher valuations of math are more likely to view STEM careers as feasible (Maltese & Tai, 2011). When these career options seem realistic, they are more likely to adjust their educational expectations and major choice in order to achieve their career aspirations (Gottfredson, 1981; 1996). Also notable is that not only was math attainment a significant predictor, but students with disabilities had significantly lower attainment values than their peers without disabilities. Science intrinsic value was closely associated with interest in science. This meant that students with disabilities who reported being more interested in science were also more likely to intend to declare a STEM major when they enrolled in college. These results corroborate previous research that has shown subject area interest to be stronger predictors of subject persistence than achievement scores (Simpkins, Davis-Kean, & Eccles, 2006).

Moderation Effects

Two interaction terms were included to detect moderating effects of disability types on the influence of demographic and expectancy-value factors on students' intentions to declare STEM majors. Both of these terms were included based on their enhancement of model fit; however, only one was a statistically significant predictor. The significant term was the interaction of being a woman and having ADHD, suggesting that the effect of being a woman on the probability of declaring a STEM major differs for students with and without ADHD. To be clear, women with ADHD were more likely to intend to pursue STEM majors than women without ADHD.

Comparing the significance of predictors in Tables 8 and 9 is rather informative here. From Table 8, neither the ADHD indicator nor the science intrinsic value factor were significant predictors. After including the interaction effects, both of these predictors became significant conditional effects in Table 9. The introduction of the interaction terms improved the model fit because prior to inclusion, the effects of these terms were included in the error portion of the regression equation. Hence, the inclusion of the interaction terms helped to reduce omitted variable bias.

Implications

The expectancy-value model as a whole was not very informative for investigating the STEM majoring intentions of college-bound students with disabilities, as evident from the inclusion of only two calculated factors. Perhaps the poor fit of the conceptual framework was due to the measures used to represent the different constructs within the model as opposed to the model itself. The measures worked well for previous research using the HSLS:09 (i.e., Andersen & Ward, 2014), but that research was focused on a rather specific population of high-ability students. It is worth testing this model again using different data, especially if the data are also collected with the expectancy-value model in mind. While the NCES was guided by this model during question construction, several other research priorities were trying to be addressed as well. Researchers who engage in collecting data firsthand should collect several measures of each of the constructs. They should also measure math and science values separately and consider if there are other subject areas that can be tapped into. Math and science only represent two of the umbrella categories under STEM. Engineering is difficult to measure

in high school due to the lack of related coursework in many schools; however, computer science and technology courses are more accessible to students across the country.

Future researchers are encouraged to incorporate measures of disability into their research that represent the broad diversity of disability as opposed to including this identity as only a binary indicator (has a disability or does not have a disability). In addition to the models presented above, I constructed models with only a single binary indicator of having some type of disability. The disability indicator in those models never reached statistical significance, which might signal to some that disability is not an important identity to consider in STEM education. However, the models included above show otherwise. Without this approach, identifying students with ADHD as being more likely to declare a STEM major, after controlling for other background and subjective task value factors, would not have been possible. This is a new finding for students with ADHD worthy of additional attention. The results stand opposed to the prevalent deficit approach to research around the intersection of ADHD and STEM.

Math attainment and science intrinsic values were the most salient aspects of the expectancy-value model for the sample in this study. These concepts are closely associated with sense of math identity and interest in science. Middle and high school educators should take note of this finding because they are in positions to foster identity development amongst their students. Identity association can be incubated in classrooms by utilizing pedagogical approaches that make the content accessible to a wide array of learners of all ability types. Such an effort requires resources to redesign and restructure existing lesson plans that may contain inaccessible material currently. School administrators should encourage their staff to embark on this endeavor and provide

appropriate supports so that teachers can be successful in this task. Early investment in developing environments that encourage identity association with math and science among students may lead to long-term payoffs in who eventually pursues STEM majors and careers, leading to reduced underrepresentation and a greater supply for this growing component on the workforce.

This work may also help spur additional interest in science amongst students with disabilities. Interest can be fostered through the introduction of additional programs and offering a wider variety of introductory level classes in high school. Such programs would allow students to interact with science in new ways outside of the pressure of a formalized classroom experience. New programs and classes would help to introduce students to the diversity of the science field. For instance, a student may not be interested in biology or chemistry but could come to truly enjoy environmental science. However, such classes may currently only be offered to students who have completed other introductory or advanced classes. Creative ways of showing students with disabilities that they can fit into STEM fields and encouraging engagement in a variety of topics could help reverse the current trend of underrepresentation in STEM degree holders.

CHAPTER 4

INFLUENCE OF MULTIPLE FORMS OF CAPITAL ON STEM MAJOR INTENTIONS FOR STUDENTS WITH DISABILITIES

There is a continued call to better understand the pipeline students must navigate beginning in high school and flowing through college for underrepresented populations in science, technology, engineering, and math (STEM) fields. These calls are in reaction to a continual failure of the number of STEM graduates to keep pace with the growing demand and need for persons in these fields (Commission on Professionals in Science and Technology, 2007; Lowell & Regets, 2006). Over the past several decades, the number of STEM-based bachelor's degrees awarded declined (U.S. Census Bureau, 2010). The decline in awarded STEM degrees resulted in a smaller supply of workers prepared to pursue STEM careers (U.S. Department of Labor, 2007).

STEM career opportunities continue to grow, aligning with earlier projections that these fields would experience the largest growth in employment and wages by 2018 (Bureau of Labor Statistics, 2009). More recent estimates suggested that these fields will grow about 13 percent over the decade from 2012 to 2022 (Vilorio, 2014). Many of the areas where growth is expected are related to technology. Several technology-focused jobs are considered high-employment with fast-growth (e.g., software developers, computer systems analysts), meaning that many job opportunities will become available as the industry expands. The expansion of STEM career opportunities coupled with the declining degree attainment rates in associated fields created a gap between the supply of

graduates with the necessary skills and knowledge and the demand for career-ready workers.

One way to address this growing gap is to target specific populations that are not pursuing STEM at rates expected for their population sizes. The National Science Foundation (2015) highlighted people with disabilities, women, and racial minorities as underrepresented groups in STEM fields and careers. Most of the subsequent research exploring this representation has only focused on gender and race/ethnicity. This is not surprising given recent findings suggesting that students with disabilities are under-researched (Peña, 2014; Kimball, Wells, Lauterbach, Manly, & Ostiguy, 2016). However, given that persons with disabilities have an unemployment rate twice as high as persons without disabilities (Bureau of Labor Statistics, 2017), encouraging students with disabilities to pursue STEM degrees and careers could help alleviate the shortage of STEM workers and increase the number of persons with disabilities who are gainfully employed.

In addition to increasing representation of students with disabilities in STEM as a way to help meet workforce demands, there is also an equity argument to be made. Individuals with disabilities have lower median incomes than those without disabilities (Brault, 2012). STEM careers, on average, pay more than non-STEM careers (Beede, Julian, Langdon, McKittrick, Khan, & Doms, 2011; Vilorio, 2014), so encouraging more students to pursue these careers could help increase median incomes and lead to greater social mobility. The underrepresentation of students with disabilities is not merely a matter of lack of interest in STEM amongst this population. Limited research concluded that these students were, on average, as likely to declare STEM majors early in college as

their peers without disabilities (Lee, 2011). This singular finding suggested that a similar proportion of students with and without disabilities were in the STEM pipeline at the start of college; however, additional research is needed to test this conclusion, especially because of the continued underrepresentation of this population amongst STEM graduates.

Using data from the High School Longitudinal Study of 2009 (HSL:09), I explored the decision of students with disabilities to declare STEM majors upon college enrollment. Tracing the STEM pipeline beginning in high school is important because students rarely reenter the pipeline after high school and their plans serve as good predictors of degree completion (Maltese & Tai, 2011; Syed, Azmitia, & Cooper, 2011; Tai, Liu, Maltese, & Fan, 2006). Specifically, I focused on three sources of capital (human, social, and cultural) to identify areas to reinforce the STEM pipeline in an effort to repair leaks in the pipeline where students with disabilities may flow out and away from STEM-related outcomes.

Sources of Capital

Previously in educational research, human capital-based frameworks were the most commonly used theoretical perspectives to study college choice (Paulsen & Toutkoushian, 2008). Human capital theory is an economic theory that takes into account the knowledge, skills, and characteristics individuals have that contribute to their ability to productively contribute to society (Acemoglu & Autor, 2011; Becker, 1962). Knowledge, skills, and characteristics encompass innate traits as well as those acquired through experience or education. Researchers use human capital to explore the benefits of increases in education as well as the cost-benefit analysis that individuals undergo when

deciding to pursue higher levels of education (Levin, 1989). They are also interested in ways school quality and resources can help explain differing levels of capital between individuals (Acemoglu & Autor, 2011). Conceptualizations of human capital theory tend to be broad which helps adapt the theory to a range of topics; however, this also necessitates that researchers explicate what they consider to represent human capital. Human capital is useful when considering college major choice because it allows researchers to take into account high school education. For STEM majors in particular, foundational classes can be taken in high school to facilitate pursuing STEM in college.

Cultural capital theory is a sociological theory that refers broadly to cultural knowledge shared with an individual from caregivers (Bourdieu, 1986). The accumulated amount of cultural knowledge that individuals possess influences their ability to negotiate educational pathways. Cultural capital in part represents the social class that families belong to, with middle- and upper-class families maintaining the most prized components (McDonough, 1997). The amount and forms of cultural capital that individuals possess have important influences on their educational pursuits. High school students from families with little cultural capital may see a college degree as unobtainable, restricting their educational aspirations accordingly (Bourdieu & Passeron, 1977). Families with little cultural capital are likely composed of parents who did not obtain a postsecondary degree and might not have ever pursued further educational opportunities after completing high school. Higher education is not a part of the culture of these families, so students likely lack guidance from parents with insider knowledge about how the college application and enrollment processes work. Such a scenario places some students at a disadvantage as they pursue additional education. STEM-related cultural capital, such as

having a parent who majored in a related discipline in college, serves as an important resource for students as they prepare to pursue these fields themselves.

Social capital pertains to an individual's network of connections, information, and resources (Coleman, 1988; Veenstra, 2009). High school students, at minimum, belong to formal networks within their schools such as math and science classes. In these classes, teachers serve as potentially useful links between student and subject. Teachers can foster interest in their respective fields and provide useful information about future classes students may be interested or even college majors relevant to their desires. Students are more likely to tap into their connections with teachers in upper level and AP courses because they are in the process of considering and/or applying to higher education institutions. Some schools also offer extracurricular activities targeted toward student interests during which students may begin forming connections with like-minded peers. Individuals are able to draw on their networks for guidance on college choice processes such as college and financial aid applications (O'Connor, Hammack, & Scott, 2010), and it is reasonable to assume that they would do the same to seek guidance on selecting a college major.

Literature Review

Measures of human (e.g., Avery & Hoxby, 2004), cultural (e.g., Perna & Titus, 2005), and social capital (e.g., Bryan, Moore-Thomas, Day-Vines, & Holcomb-McCoy, 2011) are predictive of college going, but these forms of capital have not been explicitly identified in research focused on STEM major choice. In applied research, manifestations of capital are commonly not labeled clearly, requiring readers to identify different types of capital on their own. The following sections draw from research pertaining to course-

taking and achievement, interest in STEM subjects, and STEM classroom experiences for high school students broadly. Within these sections, I connect findings from these promising areas of research around predicting pursuit of STEM majors to these three measures of capital explicitly to demonstrate that they are useful in predicting major choice in addition to college enrollment.

Course-Taking and Achievement

Approximately 80 percent of students who completed STEM degrees chose their majors sometime during high school and/or before beginning college (Maltese & Tai, 2011; Tai et al., 2006), and the greatest amount of attrition occurred between high school graduation and the first year of college (Hilton & Lee, 1988). Current policy initiatives highlight the need to enroll more students in advanced math and science courses as well as boost subject-specific achievement scores. When students complete additional advanced STEM-related courses, their acquired human capital increases as a result of increased academic preparation. Relatedly, increasing achievement scores demonstrates that students have better grasps on their newly gained knowledge through higher levels of academic achievement. Yet, recent research suggested that this emphasis on increasing enrollment in advanced courses and achievement scores may be misguided (Maltese & Tai, 2011).

A point of disagreement in this literature is the importance of the number and level of math and science courses completed in high school. The level (i.e., difficulty) of the courses that students completed were found to matter more than the sheer number of courses completed (Madigan, 1987). In particular, science proficiency assessment scores increased significantly for students who completed high-level science courses, more so

than their peers who did not complete such courses. Students who completed challenging math and science courses tended to have high scores on achievement tests, exhibited few behavioral problems in school, and had parents with high educational aspirations for them (Schneider, Swanson, & Riegle-Crumb, 1998). These results are logical under a human capital framework. Students acquire human capital in the form of new knowledge through the completion of courses and are able to demonstrate this acquisition through achievement tests. It is also worth noting the connection to cultural capital here, where students who completed advanced classes also had parents with higher aspirations for how much education they would attain.

Completing a rigorous high school curriculum was linked to college completion (Adelman, 2006; Trusty, 2002; Tyson, Lee, Borman, & Hanson, 2007), while other studies found that the number of math and science courses taken in high school was more important than the level of courses. One such study concluded that tenth-grade students who took the most math and science courses were the most likely to plan to pursue STEM majors in college (Maple & Stage, 1991). Students who completed more math and science courses in high school were also more likely to progress into STEM majors in college (Burkam & Lee, 2003; Trusty, 2002; Ware & Lee, 1988). Because the number of math and science courses completed was found to be predictive of postsecondary completion and STEM enrollment, it is important to consider students' ability to complete such courses. Some high schools may have limited classes available for students to take. Such structural limitations may limit students' acquisition of new knowledge.

The courses students completed in high school impacted growth in math achievement; however, when background characteristics such as gender and race/ethnicity were introduced the influence of courses was minimal (Bozick & Ingels, 2007). Women who took advanced math coursework in high school were more likely to major in STEM as were men who took physics (Trusty, 2002). While women were more likely to complete advanced math coursework, they were less likely than men to complete the highest-level math courses such as calculus (Tyson et al., 2007).

Interest in STEM Subjects

In addition to course-taking patterns and subject-specific achievement, STEM major choice is linked to increased interest in STEM topics. High school students lacking interest in math and science classes are likely to become disengaged from the topical areas and ultimately view aspiring to a STEM career as unviable and undesirable (Eccles, 2009). When this occurs, students may pull back from social networks that are primarily focused on math or science, leading to losses in social capital. Holding math in a positive regard was associated with a greater likelihood of pursuing STEM for women (Ware & Lee, 1988). For men, the number of science courses was more important along with coming from a family with a high class standing and rating their educational experience positively. Families in upper social class levels are likely college educated, providing increased amounts of cultural capital for students to tap into as they decide whether or not to pursue STEM.

On average, Black and Hispanic students completed fewer high-level math and sciences courses; however, students of color who took higher level courses were as likely as White students to continue on to STEM degrees (Tyson et al., 2007). Without these

courses, racial minority students enter college with lower amounts of human and social capital. When they are able to complete high-level courses, they are able to enter college with similar amounts of the portion of human capital dealing with academic preparation. Additionally, these classes also provide students with valuable peer connections and links to teachers who may be able to provide guidance to students as they consider pursuing a major related to STEM. Despite these findings, research investigating gender and race in relation to STEM outcomes largely drew mixed conclusions (e.g., Bonous-Harnmarth, 2000; Hilton & Lee, 1988; Mau, 2003).

STEM Classroom Experiences

Encouraging high school students to complete a greater number of math and science courses and take more challenging courses is important because these courses provide students with opportunities to acquire additional human and social capital. Related to social capital, classroom experiences are also important to consider. These experiences are largely controlled by teachers and several studies identified promising practices that increased interest in STEM. Teachers can work to improve student attitudes toward math and science by incorporating hands-on activities, using a variety of pedagogical techniques, and covering a broad array of topics that will meet the interests of many students (Maltese & Tai, 2011; Myers & Fouts, 1992). When students have positive experiences in classes, they may also feel more comfortable approaching their teachers to ask for subject-specific advice, growing their social network.

Students also picked up on the enthusiasm that teachers exhibited toward their topic and benefited from discussion of future career possibilities (Woolnough, 1994). Their experiences within their science and math classes in high school may play a

considerable role in deciding who ends up pursuing STEM degrees (Cleaves, 2005). As mentioned previously, interest is an important factor to consider when investigating major choice because if students lack or lose interest in a math or science subject in high school, they may leave the STEM pipeline permanently. Even when components of human and cultural capital were accounted for, subject-specific interest was found to be a powerful predictor a students' likelihood of persisting in the subject (Simpkins, Davis-Kean, & Eccles, 2006). Along with teachers, the expectations of parents and counselors play an influential role in students' career pursuits (Mau, 2003).

STEM for Students with Disabilities

Students with disabilities are enrolling in postsecondary education at an increasing rate, with recent estimates of the proportion among college students falling between 11 and 12 percent (Snyder, de Brey & Dillow, 2016). Limited research on graduation rates for these students reports mixed results. Some find that they complete degrees at similar rates as their peers without disabilities if they make it into college (Wessel, Jones, Markle, & Westfall, 2009), while others report that students with disabilities continue to lag behind their peers without disabilities (DaDeppo, 2009; Horn & Berkold, 1999). Students with disabilities are less likely to be involved in high school activities, leading them to miss opportunities for STEM career preparation (Eriksson, Welander, & Granlund, 2007). Lack of involvement in these activities also leads to fewer opportunities to add connections to their social networks such as like-minded peers.

During high school, students with disabilities lack role models in STEM fields (Alston, Bell, & Hampton, 2002; Bonetta, 2007). Without role models, students may not see related careers as viable to them, leading to decreased interest and disengagement

with math and sciences classes and activities. Not all teachers are prepared to fully engage these students within STEM curricula (Bargerhuff, Cowan, & Kirch, 2010; Rule, Stefanich, Haselhuhn, & Peiffer, 2009). If students are not able to participate fully in class, they may miss out on acquiring new knowledge. Attempts to demonstrate academic achievement may not appropriately represent their ability to master the subject matter. Teachers unable to reach students with disabilities may see these students as less capable and attempt to dissuade them from pursuing these topics further.

For the students with disabilities who pursued postsecondary education, nine percent majored in engineering or communications and only six percent majored in science or computer-related fields (Newman et al., 2011). Among these students, individuals with autism had the highest STEM participation rates (Wei, Yu, Shattuck, McCracken, & Blackorby, 2013). While students with autism had higher STEM participation rates, they also had the third lowest postsecondary education participation rates, according to data from the National Longitudinal Transition Study-2, a study focused on postsecondary outcomes for students with disabilities. Transition planning and goal-setting have shown promise for students with autism. Students with autism whose stated primary goal in their transition plans was postsecondary education were more likely to enroll at 2- and 4-year institutions than students with autism who did not participate in transition planning and/or goal-setting (Wei, Wagner, Hudson, Yu, & Javitz, 2016).

Conceptual Model

This study was guided by human, social, and cultural capital theories which were all core elements of Perna's (2006) college choice model. Perna's model situated a

student's decision to enroll in college as occurring within four layers: a) social, economic, and policy context (layer 4), b) higher education context (layer 3), c) school and community context (layer 2), and d) habitus (layer 1). When deciding to enroll in college, individuals weigh the costs and benefits according to factors associated with each of these layers. While Perna's model was not intended to study college major choice, the innermost layers included the core components of the conceptual lens I wanted to use for this study. I was interested in the role that different forms of capital (layer 1) played in shaping major intentions as well as whether high schools with particular characteristics (layer 2) led to increased numbers of STEM-pursuing college-goers.

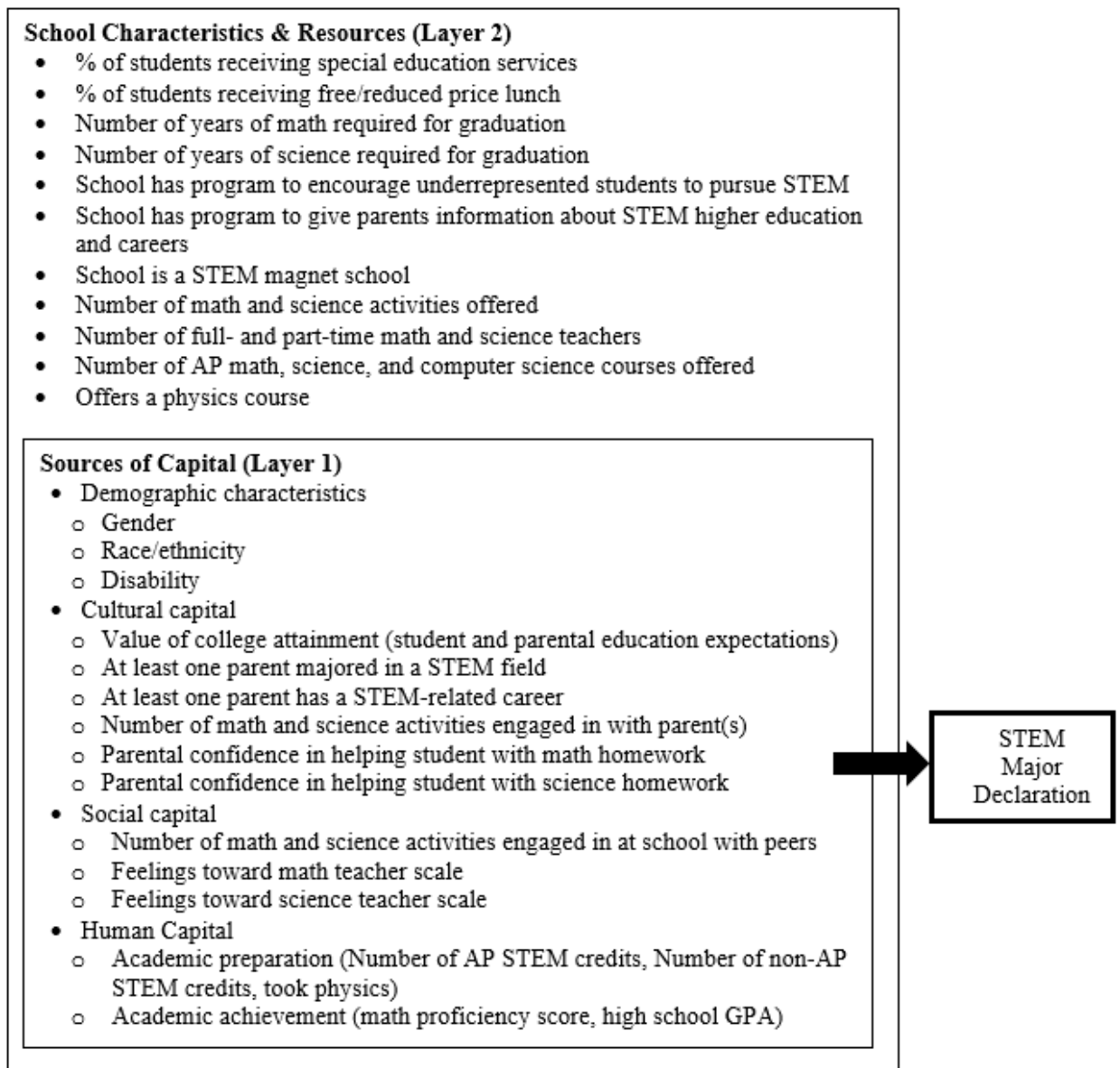
Adapting Perna's (2006) model with these interests in mind, Figure 3 presents the conceptual model used to guide variable selection and model building for the present study. The original college choice model contained four layers, whereas my adapted model contains two to account for the school and personal contexts around students' decisions to major in STEM fields. Measures included in the original model were largely not appropriate for this analysis because they pertained to characteristics that impacted students' decisions to enroll in college; however, students in my sample were already enrolled in college by the time they reported their intended majors. Therefore, my adapted model drew on various STEM-related constructs similar in vein to the original measures from the college choice model.

The second layer accounted for the school and community context by incorporating characteristics of students' high school. This layer contained measures of the percentage of students at the high school who received special education services or

received free/reduced price lunch, math and science graduation requirements, number of STEM programs, courses, and activities at school, and number of math and science teachers. The previous measures served as indicators of school resources and structural factors influencing postsecondary STEM preparation such as classes offered and teachers available. Academic intensity consistently appears as a strong predictor of eventual college graduation; however, not all students attend schools where rigorous and advanced courses are offered (Adelman, 2006). Incorporating measures of academic background is important in predicting college going and completion because there are structural factors that constrain students. The second layer of the model contained structural characteristics of high schools to account for the differences between high schools that would limit development of capital amongst their students.

The innermost layer contained measures representing human, cultural, and social capital as well as demographic characteristics. Previous applications of Perna's (2006) model have not included disability identity among their demographic characteristics (Kimball et al., 2016). Cultural capital variables were related to students' interactions with parents involving STEM activities and parental connections to STEM fields. Fewer representations of relevant social capital variables were identified. The included measures represented feelings toward students' math and science teachers and STEM-related activities they engaged with their peers. Expressions of human capital were identified and included under the subheadings "demand for higher education" and "supply of resources." These measures dealt with students' academic preparation and achievement. Research focusing on these forms of capital is highlighted in the following sections.

Figure 3. Conceptual Model of STEM Major Declaration



Sources of capital are under-researched for students with disabilities, and Perna's (2006) college choice model has yet to be applied to students with disabilities specifically (Kimball et al., 2016). The present chapter sought to address these gaps by exploring how forms of capital differed for students with disabilities across disability types as well as compared to students without disabilities. Analysis also fits the adapted conceptual model

presented in Figure 3 to students with disabilities. The following questions guided this analysis:

- To what extent do descriptive differences exist between students with and without disabilities for measures of human, cultural, and social capital?
 - To what extent do descriptive differences exist across disability types for measures of human, cultural, and social capital?
- To what extent do human, social, and cultural capital (layer 1) influence students with disabilities' intentions to declare STEM majors?
 - To what extent do the relationships between sources of capital and intention to declare a STEM major differ by type of disability?
- To what extent do high school STEM characteristics (layer 2) influence students with disabilities' intentions to declare STEM majors?
 - To what extent do the relationships between high school STEM characteristics and intention to declare a STEM major differ by type of disability?

Method

To address the above questions, I used data from the HSLs:09, sponsored by the National Center for Education Statistics (NCES). Two full waves of data collection were completed in addition to an update to capture high school outcomes and postsecondary plans at the time of this study. During the first two waves, students and parents completed surveys; in addition, administrators and counselors completed questionnaires during the first wave. The majority of the data pertained to the high school experiences of students across the country; however, with the 2013 update, initial college information was

recorded, such as entry and major declaration (Ingels et al., 2015). This update took place during the summer following high school graduation and the beginning of college for study participants. These data were the latest in a lengthy history of longitudinal studies beginning in high school and following students through postsecondary education. HSLs:09, with its wide array of measurements at the high school level, was the most appropriate dataset to answer my questions.

Sample

Approximately 24,000 students participated in the base-year of data collection for the HSLs:09 (Ingels et al., 2105). Ultimately, students with any type of disability made up my population of interest, so the disability-related measures I was able to use to narrow my sample in this manner were particularly important. Instead of asking students to self-identify as having a disability, parents were asked to report whether they had been informed that their child had any of several identified forms of impairment. Included forms were: a) learning disability, b) developmental delay, c) autism, d) hearing/vision problem (i.e., sensory impairment), e) bone/joint/muscle problem (i.e., mobility impairment), f) intellectual disability, and g) ADD/ADHD. However, two of these categories (autism and intellectual disability) contained very few respondents. As a result, these forms of disability could not be used during imputation or analytic procedures and were excluded. The decision to exclude these students as opposed to combine multiple identity categories was driven by the desire to produce results that were clearly attributable to any individual disability experience. A combined category would not be able to achieve this desired clarity, particularly because of prior research indicating that students with autism in particular are likely to pursue STEM fields. By combining these

students with any other group, any potential increased likelihood might be assumed to be driven by these students. The five identities used were: a) learning disability, b) sensory impairment, c) mobility impairment, d) ADHD, and e) developmental delay. Each form of disability was included in my analysis as a binary indicator.

The analytic sample included only students who enrolled in college; keeping only those who were enrolled in postsecondary education resulted in a loss of 11,730 students, nearly half of the original sample. Only students who indicated that they were enrolled were asked the question pertaining to intentions to declare specific majors. A large number of parents did not respond to the base-year survey, meaning that no disability data were collected for many students. I excluded students whose parents failed to respond to the survey or the items pertaining to disability, resulting in a further trimming of my sample by 3,140 students. Aside from the disability- and postsecondary-related items, my included measures were captured during the first follow-up of data collection. Students who did not complete this questionnaire were excluded, as were students who were not taking a math and/or science class during the semester of survey administration. Students not taking these classes were excluded because the feelings toward math and science teacher scales were formed using questions only asked of students taking math and science. Applying the above exclusion criteria, my resulting analytic sample size was 7,820 students.

After reducing my sample in these ways, the number of students identified as experiencing each included type of impairment was: learning (390), sensory (140), mobility (190), ADHD (480), and developmental (190). Disability types were not mutually exclusive, and approximately 28 percent of students identified as having a

disability experienced multiple forms of impairment. Students were allowed to belong to multiple disability identity groups to acknowledge the different challenges that students would face depending on their impairment(s). Condensing the 28 percent down into a multiple disabilities category to make all impairment categories mutually exclusive would have resulted in meaningless interpretations for the condensed category. Sample sizes were small, so standard error estimates were examined during model building to detect any potential inflation due to sample size constraints. Inflated standard error estimates would indicate potential instability in my model.

Missing data remaining following sample restriction was handled through multiple imputation following current best practices in higher education research (Manly & Wells, 2015). A fully conditional imputation model was used for this process which incorporated design weights in order to account for the clustering of the data (Reiter, Raghunathan, & Kinney, 2006; van Buuren, 2007). Prior to imputation, complete case analysis would have resulted in only 50 percent of the sample being available. In total, 50 datasets were imputed because researchers are encouraged to impute as many datasets as the percentage of missing data (Bodner, 2008). Across variables with missing data, rates of missingness ranged from a low of 2 percent up to a high of 19 percent. The variable with the most missing data was the count of advanced placement (AP) classes offered by high schools. These data were missing due to high school administrators who opted not to complete the survey. Similarly, this resulted in missing data on other measures representing school characteristics such as math and science graduation requirements and number of STEM activities sponsored by the school.

Variable Inclusion

Cultural capital variables included student and parental educational expectations (representing the value of college attainment), whether at least one parent majored in a STEM field, and whether at least one parent worked in a STEM field. STEM careers were classified based on O-NET categorization, and STEM majors were determined using the Immigration and Customs Enforcement's (ICE) guide. The ICE (2016) guide is commonly used by international students studying in the U.S. and academic programs to correctly identify major type for visa paperwork. I used this guide because no approach to identifying STEM-related majors based on the 2010 classification of instructional programs codes could be identified at the time of this study. The ICE guide was created by a government-sponsored organization and was assumed to be a valid classification approach.

Social capital variables focused on student actions and perceptions including: number of STEM-related activities engaged in with peers and scales of perceptions of their math and science teachers. Activities included participating in math and/or science clubs, study groups, summer camps, and/or competitions. Participation in these activities represented a look into the social network of students and potentially influential peers. Scales contained student responses to the following statements: a) teacher makes [math/science] interesting, b) teacher makes [math/science] easy to understand, c) teacher wants students to think not memorize material, and d) teacher does not let students give up. Students responded on a four-point Likert-type agree-disagree scale. Factors were fit using exploratory factor analysis, and alpha coefficients for the scales were .84 for math teacher perceptions and .85 for science teacher perceptions.

Guided by Perna's (2006) model, human capital was conceptualized as encompassing academic preparation and academic achievement. Measures of academic preparation included the number of AP and non-AP STEM credits earned in high school and whether students took physics in high school. Academic achievement was represented by scores earned on math proficiency tests and the students' cumulative high school GPAs.

In terms of demographic characteristics of students, seven dichotomous variables were included, indicating whether a student identified as a woman, as a racial minority, or were identified as having any of the five disability types mentioned previously. Gender, racial, and disability identities were included because of the NSF's (2015) continued declaration that these populations are underrepresented in STEM degree fields in addition to my focus on disability. My dependent variable was a binary indicator of whether students intended to declare a STEM-related major upon matriculation, coded by the NCES.

Analytic Approach

The initial method of analysis to model intent to major in a STEM field was hierarchical generalized linear modeling (HGLM). The model had a binomial distribution and utilized a logit link due to the dichotomous nature of the dependent variable. This HGLM approach was appropriate because the dependent variable was binary, students were nested within schools (Heck, Thomas, & Tabata, 2010), and using this approach would allow for more accurate estimates (Raudenbush & Bryk, 2001). By modeling this nested structure within the HGLM framework as opposed to linear regression, I was able to simultaneously estimate individual and group-level variance.

However, after fitting the HGLM, model statistics suggested that the approach was not necessary. Fitting the intercept-only model revealed a low intraclass correlation (ICC) of .045. The ICC suggested that only 4.5 percent of the variation in the percent of students intending to declare STEM majors was attributable to the schools attended. While low, the ICC alone is not always a good sole indicator of the necessity of hierarchical modeling. Instead, researchers are encouraged to calculate the design effect statistic following the formula set forth by Muthén and Satorra (1995). In education research, a common rule of thumb is that if the design effect statistic is lower than two, hierarchical modeling is unnecessary (e.g., Bonnet, Goossens, & Schuengel, 2011; Kilian, Hofer, & Kuhnle, 2010; Peugh, 2010). The calculated design effect statistic for my model was 1.5. In other words, the sampling variance of an estimated statistic in my model would be 1.5 times larger than if the respondents had been drawn from a random sample.

As a result of a low ICC and a design effect with a value less than 2, I decided to move away from HGLM to multiple logistic regression. My logistic regression model only included students identified as having at least one type of disability. Using Stata 14's *svyset* command, I was able to produce estimates which accounted for the complex nature of the sampling design of the HSLs:09. Estimates incorporated the primary sampling unit, sampling stratum, and student analytic weight. Accounting for the sampling approach in this manner allowed for more accurate variance estimates. First, a base model was fit which only included demographic characteristics. Model building then proceeded by including each of the variables from my conceptual model individually. Variables were retained in the model based on Chi-squared model comparison tests.

Significant changes in Chi-squared values indicated that measures contributed to a greater model fit (Menard, 2002). Following the inclusion of these variables, I tested interaction effects between disability types and retained capital variables in the model following the aforementioned Chi-squared model comparison process (Jaccard, 2001). This was done in order to identify potential moderation effects of disability type on the influence of a predictor on the outcome variable. Interaction effects were also tested between disability types and gender and racial identity because of the underrepresentation of these populations in STEM and the assumption that disability would further reduce a woman's or racial minority's likelihood of majoring in a STEM field.

Results

Before fitting the logistic regression model predicting students' intentions to declare STEM majors, I conducted means comparisons between students with and without disabilities as well as across disability types. All variables were mean centered to aid in interpretation. Table 10 contains the calculated differences between groups that resulted from these comparisons. Because the disabilities categories were not mutually exclusive, comparisons were conducted for each disability category separately. For each included difference in Table 10, the value represents how the column group compared to their respective reference group. Reference groups for each disability identity were their opposite groups (e.g., students with learning disabilities were compared to students without learning disabilities, students with no disability were compared to students with any type of disability).

To illustrate how Table 10 should be interpreted, the calculated difference for proportion majoring in STEM for students with learning disabilities was -0.04. This

meant that the proportion of students with learning disabilities intending to declare a STEM major was 4 percentage-points lower than students without a learning disability. Additionally, students with no disability (labeled “None”), had a difference for proportion majoring in STEM of 0.02. This meant that the proportion of students with disabilities who intended to declare a STEM major was 2 percentage-points higher than students with any type of disability. Thus, the final column is similar to comparisons between students with and without disabilities in other research that includes disability in a binary fashion.

Demographic and Outcome Comparisons

Two demographic variables were included in initial comparisons: gender and racial identity. No statistically significant differences were detected based on racial identity of students with or without disabilities, nor across disability types. For students without a disability, a higher proportion identified as women ($p < 0.01$). Significant differences were also found across disability types. Students with learning ($p < 0.05$), ADHD ($p < 0.01$), and/or developmental disabilities ($p < 0.05$) were less likely to identify as women. Comparing students with and without disabilities in terms of the outcome variable, the difference was not statistically significant. Differences across disability types were also not statistically significant. See Table 10 for complete results.

Capital Comparisons

Moving onto comparisons across the three forms of capital, sources of cultural capital were first considered. The first two of these measures were concerned with the educational expectations that students had for themselves and the expectations their parents had for them. Both students without disabilities and their parents, on average, had

higher educational expectations for the student than did students (or parents of students) with any type of disability ($p < 0.01$). Across disability types, similar expectations were expressed by students themselves and their parents. For brevity, I only mention the students' expectations. Students with learning ($p < 0.01$), ADHD ($p < 0.01$), and/or developmental disabilities ($p < 0.01$) expected to pursue significantly fewer years of education than their comparison groups. The two remaining sources of cultural capital were whether at least one of the students' parents majored in STEM in college or had a STEM-related career. Respondents identified as having developmental disabilities were less likely than their peers without developmental disabilities to have at least one parent who majored in STEM ($p < 0.05$). Students with sensory impairments were less likely than their peers without sensory impairments to have a parent who had a STEM-related career ($p < 0.05$).

Representing social capital, the amount of STEM-related activities students participated in with their peers was calculated. Students without disabilities participated in significantly more of these activities than did students with any type of disability ($p < 0.01$). The students with ADHD in particular participated in significantly fewer of these activities, on average ($p < 0.01$). Two scales were estimated that represented students' feelings toward their current math and science teachers. Overall, students without disabilities had higher than average feelings toward their math and science teachers than students with any disability ($p < 0.05$). Students with ADHD's feelings toward their math teachers were significantly below average ($p < 0.05$).

Table 10. Descriptive Comparison Differences across Disability Types^a

	Disability Categories					
	Learning	Sensory	Mobility	ADHD	Develop- mental	None
STEM major	-0.04	0.00	-0.08	0.05	-0.01	0.02
Woman	-0.10*	-0.11	0.03	-0.25**	-0.14*	0.13**
Under-represented racial minority	0.05	-0.02	0.10	-0.04	0.10	0.00
Student educational expectations	-0.80**	0.00	-0.36	-0.41**	-1.23**	0.48**
Parental educational expectations	-0.67**	-0.12	-0.05	-0.52**	-0.57**	0.43**
At least one parent majored in STEM	-0.03	-0.02	-0.03	0.02	-0.04*	0.01
At least one parent has STEM career	-0.02	-0.05*	-0.03	0.01	-0.02	0.01
STEM activities with peers	-0.10	-0.13	0.00	-0.24**	-0.21	0.18**
Feelings toward math teacher scale	-0.19	0.10	-0.26	-0.22*	0.00	0.15*
Feelings toward science teacher scale	-0.15	0.10	-0.11	-0.16	-0.19	0.12*
AP STEM credits	-0.39**	-0.21*	-0.33**	-0.42**	-0.44**	0.40**
Non-AP STEM credits	-0.53**	0.15	-0.87**	-0.32*	-0.71**	0.49**
Took physics	-0.14**	-0.13*	-0.14*	-0.08*	-0.14	0.11**
Math proficiency	-0.94**	0.00	-0.47**	-0.46**	-1.08**	0.55**
High school GPA	-0.46**	-0.01	-0.24*	-0.42**	-0.43**	0.36**
Family income	-0.24	0.06	0.34	0.16	-0.89	-0.02

Notes. n = 7,820; imputations = 50; weight = W2STUDENT; * p < 0.05, ** p < 0.01; All continuous variables and scales centered to a mean of zero. ^a reference groups are the opposite (e.g., the reference group for students with learning disabilities is students without learning disabilities)

The final source of capital included in this analysis was human capital, and numerous statistically significant differences were identified. Across measures of AP and non-AP STEM credits earned, whether students took physics in high school, math proficiency scores, and high school GPAs, students without disabilities had higher

average values than students without disabilities ($p < 0.01$). While students with learning disabilities, mobility impairments, ADHD, and/or developmental disabilities had lower average values on these measures as represented by the negative differences, students with sensory impairments differed on fewer measures. These students only completed fewer AP STEM classes ($p < 0.05$) and were less likely to take physics ($p < 0.05$) than their reference group. Refer to Table 10 for complete results.

Predicting STEM Majoring for Students with Disabilities

In the base model, only demographic characteristics were included. Gender and having ADHD were the only significant predictors in this model. Being a woman resulted in lower odds of intending to declare STEM majors, while the odds for students with ADHD were higher. Based on this initial model, the probability of a woman intending to declare a STEM major upon college enrollment was only 9 percent; the probability for a student with ADHD was 41 percent. Results from this model are contained in Table 11. From this model, I added additional measures individually based on the variable from my conceptual model which contributed to the greatest increase in the model Chi-squared value. In total, four variables from the conceptual model were added as well as one interaction term. Despite these variables contributing to a greater model fit, not all were significant predictors.

In the full model (see Table 12 for complete results), having ADHD was the only disability identity that was found to be a significant predictor. Students with ADHD had higher odds of intending to declare STEM majors upon postsecondary entry. When everything else in the model was held constant, students with ADHD had a probability of pursuing a STEM degree of 43 percent. In comparison, when all variables in the model

were held at zero (i.e., man, White, multiple disabilities, neither parent majored in STEM, earned an average number of non-AP STEM credits, held average feelings toward math teacher, and parent had average educational expectations for them), the probability of pursuing a STEM major was only 24 percent.

Gender remained a statistically significant predictor; being a woman was associated with lower odds of pursuing STEM. Women had a probability of pursuing a STEM degree of 10 percent when all other variables were controlled. Two of the included measures of capital were significant predictors: parent's educational expectations and the number of non-AP STEM credits students completed in high school. Both of these predictors were associated with increases in odds of pursuing STEM majors. Students whose parents' educational expectations for them 1-unit higher than average had a probability of pursuing STEM of 30 percent, an increase of 6 percentage-points over the default (i.e., reference categories for indicator variables and averages for interval variables). Students who took one more non-AP STEM class than average saw an increase in their probability of pursuing a STEM major of 28 percentage-points. A revised conceptual model is presented in Figure 4.

Table 11. STEM Major Declaration Intention with Demographic Characteristics, Odds Ratios

Measure	Odds Ratio	Standard Error	t
Learning Disability	0.91	0.24	-0.35
Sensory Impairment	1.41	0.47	1.03
Mobility Impairment	1.12	0.47	0.27
ADHD	1.73*	0.46	2.06
Developmental Disorder	1.29	0.44	0.75
Woman	0.26**	0.07	-5.02
Underrepresented Racial Minority	0.66	0.21	-1.34
Intercept	0.40	0.12	-2.94

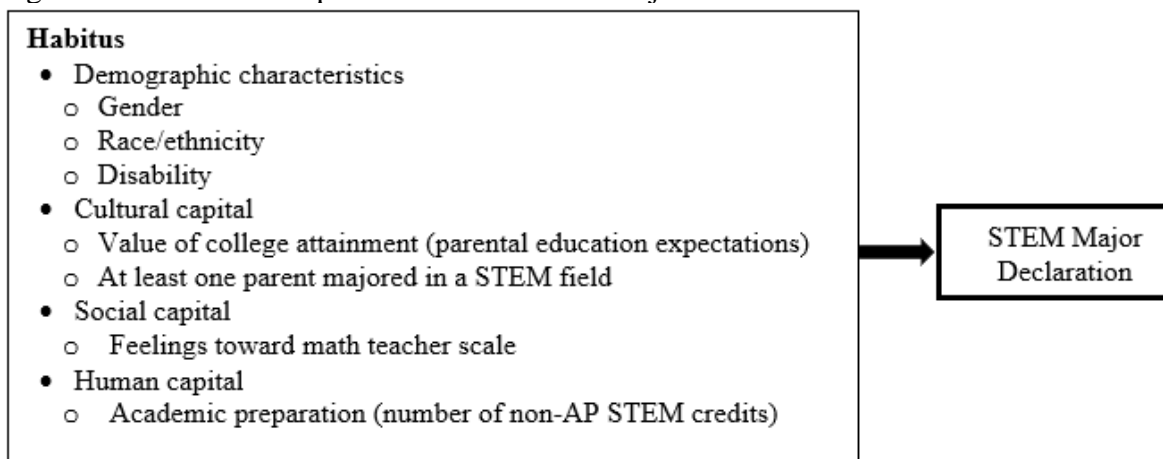
Notes. n = 1,080; imputations = 50; weight = W2STUDENT; * p < 0.05, ** p < 0.01; F(7, 192.0)

Table 12. STEM Major Declaration Intention with Demographic Characteristics, Sources of Capital, and Interactions, Odds Ratios

Measure	Odds Ratio	Standard Error	t
Learning Disability	1.01	0.28	0.04
Sensory Impairment	1.30	0.43	0.80
Mobility Impairment	1.16	0.46	0.37
ADHD	2.35*	0.78	2.56
Developmental Disorder	1.45	0.50	1.07
Woman	0.35**	0.14	-2.71
Underrepresented Racial Minority	0.82	0.26	-0.62
Feelings toward Math Teacher	0.86	0.09	-1.35
Parent's Educational Expectations	1.33*	0.16	2.35
Non-AP STEM Credits	1.23**	0.09	2.76
At Least One Parent had STEM Major	1.88	0.62	1.90
Woman x ADHD	0.34	0.20	-1.84
Intercept	0.32	0.11	-3.34

Notes. n = 1,080; imputations = 50; weight = W2STUDENT; * p < 0.05, ** p < 0.01; F(12, 193.7)

Figure 4. Revised Conceptual Model of STEM Major Declaration



Discussion

This study focused on the influence of three sources of capital (human, social, and cultural) on students' intentions to declare STEM-related majors upon enrolling in postsecondary education. To facilitate the investigation of these influences, I adapted Perna's (2006) model of college choice which contained the three sources of capital as well as high school characteristics. Using the HSLS:09, I focused on student- and school-level characteristics represented within the dataset. Due to the nested nature of these data, I initially attempted to fit the model utilizing HGLM. However, I ultimately utilized multiple logistic regression and accounted for the nested sampling strategy through Stata's *svy* command.

Sources of Capital across Disability Types

A number of differences were found between students with disabilities overall and their peers without disabilities on the measures of capital included in my original adapted conceptual model. Educational expectations for students with disabilities were significantly lower than students without disabilities, as expressed by themselves and their parents. Lowered expectations also extended to specific disability types. Students

with ADHD, learning, and/or developmental disabilities did not expect to get as far in school as their peers without these disabilities, beliefs shared by their parents.

Compared to students with disabilities overall, those without disabilities participated in significantly more STEM-related activities with other students. The only disability identity associated with participating in significantly fewer of these activities was the ADHD category. Lack of participation in these activities leads to fewer connections with like-minded students, reducing the ability of their social networks to provide support if they intend to pursue STEM. Students with disabilities, in general, also had lower than average feelings toward their math and science teachers. If students have weak connections to their teachers, they may be hesitant to turn to them for advice or recommendations when considering STEM fields in postsecondary education.

The most prominent area of capital where students with disabilities displayed differences when compared to students without disabilities was human capital. Across these measures, students with disabilities completed fewer than average AP and non-AP STEM credits and demonstrated lower levels of academic achievement than students without any disabilities. These differences were also present across most disability types. Considering previous work demonstrating the association between the number of STEM courses and achievement with the eventual decisions to major in STEM (Burkam & Lee, 2003; Trusty, 2002), these differences were troubling and potentially indicative of why students with disabilities are underrepresented amongst STEM degree holders.

Influence of Forms of Capital on STEM Intentions

Several measures of capital proved to be important influences on intention to declare a STEM major for college-bound students with disabilities. Two cultural capital

variables were retained in the final model. As parents' educational expectations for their children increased (i.e., they expected them to earn more advanced degrees) so did students' likelihoods of declaring a STEM major. Students who had parents with STEM-related majors were more likely than students without STEM-majoring parents to intend to declare STEM majors. Parents act as important role models and holders of knowledge about how to navigate college processes. Students may also become aware of potential STEM majors through conversations with their parents. Students with disabilities often lack STEM role models in high school, restricting their interest in pursuing STEM (Alston et al., 2002; Bonetta, 2007); however, parents may be able to fulfill that role.

Only the scale of feelings toward students' math teachers was retained as an indicator of social capital. Similar to parents, teachers also serve as important sources of information for students aspiring to college degrees. However, students who feel that their teachers are less supportive may not consider this important connection and source of insider knowledge. The retention of this scale and the indicator of a parent majoring in STEM were indicative of the importance of support networks. In the full model, both of these measures were retained because they contributed to a better fitting model but neither was a significant predictor. The results of the Chi-squared model tests suggested that these measures may be useful for future research.

The number of non-AP STEM credits students earned while in high school was the only retained measure of human capital. This measure was significant, indicating that as the number of classes students completed increased, the odds of pursuing a STEM major in college increased. This result jibed with previous research emphasizing that encouraging high school students to complete more STEM-related classes would result in

higher likelihoods of moving on to related fields in college (Burkam & Lee, 2003; Maple & Stage, 1991). Retention of the number of non-AP classes as opposed to AP classes suggested that the number of courses completed was more important than the level of such courses.

A surprising result from this study was the lack of the participation in STEM-related activities by students and school-based provision of such activities variables in the final model. Previous research indicated that students with disabilities were less likely to participate in extracurricular STEM activities, leaving them less-prepared to pursue related majors in college (Eriksson et al., 2007). My results suggested that students with disabilities were less likely to participate in STEM activities with their peers. However, lack of inclusion in my final model suggested that participating in these activities may not be as important as portrayed by previous research relative to other factors such as completing non-AP STEM courses and having parents that majored in STEM during college, at least for students with disabilities.

Influence of School Characteristics on STEM Intentions

Corresponding with the decision to move away from hierarchical modeling, no school-level variables were retained in the revised conceptual model. When these variables were added individually, no characteristics significantly added to the overall fit of the model. There were also no descriptive differences across these measures by disability type. These results suggest that the variability in intentions to declare STEM majors has little to do with the schools themselves and more to do with student traits.

The omission of all school characteristics was an unexpected result. Previous research emphasized the importance of looking beyond merely the classes that students

complete to the structures in place that allow students to take the classes at all. Not all schools have upper-level courses such as calculus, physics, or even AP STEM courses (Adelman, 2006). Including whether or not such classes were offered in the second layer was an attempt to acknowledge such prompting by previous research. Measures of special education support and community affluence in the form of percentage of students receiving reduced price lunch were also not useful in my model. Programs meant to encourage STEM participation and provide information to parents about college were not retained. Neither were the number of STEM-related activities sponsored by the school, suggesting that providing students with additional ways to engage in STEM material was not influential to their likelihood of majoring in these fields upon entering college.

Implications

From these results, a number of implications can be drawn for school administrators, teachers, parents, and future researchers. For administrators, the overarching lack of school characteristic variables in the final model was eye-opening. The within-school effects, which more directly impact students, appeared to be more influential in steering students toward STEM in college. These direct impacts include things such as interactions with teachers and peers. School-wide programs and initiatives aimed at increasing interest in pursuing STEM should refrain from simply adding more math and science activities and teachers; instead, resources should be aimed at enhancing pedagogy and offering a wider variety of STEM classes. Such initiatives should incorporate teachers into the decision-making process to help structure what changes to pedagogy could look like in the classroom. Creating classroom environments where all students, regardless of ability, can learn and be encouraged to actively engage in the

curricula may facilitate boosting students with disabilities' feelings toward their math teachers.

While the class-taking behavior of students was significant, it is important for schools to design curricula that allow students the ability to take a range of classes during their secondary education. Students attending schools with greater variety and quantity of such classes are at an advantage. A greater number of classes increases the likelihood that classes will fit into students' schedules, and with access to a wide variety of topics, students will be exposed to more STEM-related options that may appeal to them. For instance, students may come to find that they really enjoy computer science but not physical or biological sciences.

As postsecondary institutions work to become more accessible to students of all abilities, more information needs to be shared with high school students and their parents. From my results it was clear that students with disabilities were still holding negative perceptions about their ability to achieve in college. Highlighting available accommodations and learning resource centers could demonstrate to students that assistance is available if needed. Additionally, providing students with disabilities with connections at an institution such as a faculty member or member of an admissions staff will help to build their social network that they are able to tap into when they have questions or need guidance around postsecondary education.

Future researchers should consider incorporating structural, behavioral, and psychological measures into a single model. While not the focus of this study, the persistently low odds ratio for women declaring STEM major is troubling. The interaction term between being a woman and having ADHD significantly improved the

fit of my model, despite not being statistically significant. Incorporating multiple perspectives (e.g., behavioral and psychological) may help further investigate the relationship between being a woman and having ADHD.

Additionally, researchers should incorporate multiple dimensions of disability instead of simply including this identity as a binary indicator of the presence of an identified disability. The models discussed above were also run with only a single binary indicator of having some type of disability, producing results which lacked any statistical significance around disability. Had I not broadened my approach to including disability, the results would have signaled that disability was not as important of an identity characteristic to consider when modeling intentions of majoring in STEM. As an additional bonus, by including an array of disability types, students with ADHD were identified as being more likely to declare a STEM major, after controlling for other background and subjective task value factors. This finding, along with the interaction between having ADHD and gender, is worth supplementary attention.

In the full model, the impact of being an underrepresented minority student on the likelihood of pursuing a STEM major was reduced to statistical non-significance, yet the significance of being a woman remained. Perhaps modeling women's STEM aspirations according to measures of capital is inappropriate and a model incorporating attitudes and beliefs would be more informative. Overall, considering the influence of several types of capital on students' intentions to declare STEM majors was useful. However, Perna's (2006) full college choice model, even when adapted, seemed a poor fit for modeling my outcome of interest. Instead of focusing on the full model, narrowing the scope to only layer 1 is advised where a range of sources of capital can be included as opposed to

fitting a model looking at only a single type. Descriptive results lend support to Lee's (2011) assertion that students with disabilities were as likely to major in STEM as students without disabilities. However, I focused on only students with disabilities and found that students with ADHD were more likely to intend to pursue a STEM major upon college entry. Future researchers are encouraged to find ways to focus solely on disability and include disability innovatively into their models.

CHAPTER 5

DISCUSSION, RECOMMENDATIONS, AND IMPLICATIONS

The number of students entering postsecondary education with a disability is rising (Snyder & Dillow, 2013; Snyder & Hoffman, 2001; Snyder, de Brey, & Dillow, 2016); however, the rise in this population has not coincided with increased representation in STEM majors and careers. The National Science Foundation (2015) continues to highlight individuals with disabilities as an underrepresented population across STEM disciplines. Declining numbers of STEM graduates in general has led to an insufficient supply of workers to fill STEM careers (U.S. Department of Labor, 2007), resulting in a gap between graduate supply and workforce demand. The unemployment rate for persons with disabilities is twice as high as the rate for persons without disabilities (Bureau of Labor Statistics, 2017), creating another gap in the workforce. Further, the median monthly income for individuals with disabilities is significantly lower than the income of those without disabilities (Brault, 2012).

This dissertation attempted to address the gap between STEM workforce supply and demand as well as the employment gap for individuals with disabilities. At the beginning of this dissertation, I suggested that these problems could be addressed simultaneously with a single solution: encouraging more students with disabilities to pursue STEM majors during college. Diminishing both gaps with a common solution provides the added benefit of efficient use of resources, especially if general funds exist for increasing STEM interest and talent but not necessarily for individuals with disabilities specifically. Limited research suggested that students with disabilities were as

likely as their peers without disabilities to declare STEM-related majors early in college (Lee, 2011). In my dissertation, I did not take this finding as a given because the result was reached by only a single study. I investigated this pattern myself as well as narrowing my focus to only explore what factors encourage pursuit of STEM majors for students with disabilities.

To investigate potential solutions, I utilized commonly-employed theoretical frameworks in education research, yet to be employed when studying disability. I used data from the National Center for Education Statistics' (NCES) High School Longitudinal Study of 2009 (HSLs:09), which began data collection while students were in ninth grade and continued as they progressed through college (Ingels et al., 2015). I was primarily interested in answering an access question around what influences shaped students' decisions to pursue STEM majors upon enrollment in college. Because of my access focus, using data which followed students through high school and into college was the most appropriate.

As I embarked on this investigation to identify influences, I was guided by the following overarching question: What factors are most influential for students with disabilities as they decide to declare a STEM major upon enrolling in college? Given the differing ways that disability is defined across policies, laws, and research, my first task was to carefully consider the definitions used in the HSLs:09 as well as the measurement approaches utilizing those definitions. Once this was completed, I proceeded to fit two separate models including only students with disabilities. The first of these models tapped into the psychological realm of influences while the second considered structural ones.

Each of these chapters is reviewed below, followed by the identification of overarching takeaways and implications.

Individual Chapter Review

Chapter Two: Disability in Education Research Using National Datasets:

Definition and Measurement Considerations

Throughout this dissertation, I engaged in secondary data analysis; I was reliant on data collected by the NCES for purposes other than my own research. Therefore, gaining an understanding of how the data were collected and how variables of interest such as disability identity were measured was particularly important. In Chapter Two, I took a critical look at disability measurement in my selected dataset, the HSLs:09, and began to unpack implications that measurement would have on my results in Chapters Three and Four as well as other studies focusing on disability more broadly.

The purpose of this chapter was to highlight the importance of disability definition and measurement in survey research, with a focus on large, national surveys. I reviewed ways disability was defined and measured in previous surveys, mostly outside of the realm of education. Survey research methods literature was incorporated into the reviews; previous studies have neglected this body of research, despite its clear applicability. Following these reviews, I critically assessed the definitions used in the HSLs:09 to define disability and the measurement approaches to disability-related questions. Several important observations were made that impact the ways disability researchers are able to use these data to explore educational outcomes.

Perhaps the most problematic measurement issue was the use of parents as proxies for capturing disability identification. In the parent survey administered during

the base-year of data collection, parents were asked to identify if they had been informed that their child had a number of impairments. Additionally, they were asked to report the degree of difficulty their child experienced around several school-related activities. Parental proxy reporting of the degree of difficulty questions was a task that parents were not informed well enough to complete accurately. During data collection, rates of parental nonresponse were very high, limiting the availability of disability identity data. Missing data was of particular concern for my dissertation because of an already small proportion of students in the dataset who had some form of identified disability.

Parents were asked whether their children had any of seven different types of impairment; however, these types overlapped conceptually resulting in response options that were not mutually exclusive. The main source of overlap was the inclusion of developmental delay as an impairment type, which the Centers for Disease Control and Prevention uses as an umbrella term for several other types. Many of the impairment types that fall under the umbrella of developmental delay were also included on the survey, calling into question the validity of any of those measurements separately. The combination of the high rates of missing data and the overlapping impairment types forced me to consider which types were viable and valid for inclusion in Chapters Three and Four.

Chapter Three: Influence of STEM Valuation and Success Expectations on Major Declaration for Students with Disabilities

My third chapter delved into the influence of psychological constructs on students' intentions to declare STEM majors upon enrollment in college. I utilized Eccles and colleagues' (1983) expectancy-value framework as an analytic lens. Within this

framework, I focused on two components: subjective task value and expectations for success. In my application of this framework, both components were focused on STEM, primarily math and science. I modeled my approach after work conducted previously using the HSLs:09, which focused on these components and how they related to the outcomes of high-achieving high school students (Andersen & Ward, 2014). One of the motivations for using the expectancy-value framework was its widespread use in education but lack of consideration of disability in previous research.

To model the expectancy-value framework, I included the following factors: a) math and science attainment values, b) math and science utility values, c) math and science intrinsic values, d) non-financial STEM cost, and e) math and science self-efficacy. During design of the HSLs:09 survey instruments, subjective task value was a consideration (Ingels et al., 2015), so the NCES included several related factor scores in the dataset. Using the items identified by the NCES (Ingels et al., 2015) and Andersen and Ward (2014), I conducted factor analyses for each of my included factors, calculated internal reliability values, and created scales based on the mean value across included items for each factor. I compared internal reliability and scale values across disability types before building a logistic regression model to predict STEM major declaration intention for college-bound students with disabilities.

Few statistically significant differences were detected when comparing the mean scale values across disability types, with the majority of differences found amongst students with learning or developmental disabilities or ADHD. Students with learning disabilities placed lower valuations on math attainment than students without learning disabilities. The same was true for students with ADHD and/or developmental

disabilities. Students with learning and/or developmental disabilities also rated their math and science self-efficacy lower than students without learning disabilities. Students with learning, ADHD, and/or developmental disabilities reported higher non-financial costs related to pursuing STEM than students without any of these impairments. Students with ADHD had, on average, lower math intrinsic values than students without ADHD.

From the logistic regression model, I discovered that students with ADHD were more likely to pursue STEM majors upon college enrollment, once everything else in the model was held constant. Only two subjective task value factors were retained in the final model: math attainment and science intrinsic value. The significance of math attainment value is particularly noteworthy because students with learning, ADHD, and/or developmental disabilities all had lower average values on this measure. When students placed greater value on math attainment, they were more likely to intend to pursue STEM majors in college. Given the already lower than average valuation for several disability types, working to increase this aspect should be prioritized. Students with ADHD were more likely to pursue STEM majors. The effect of being a woman on the likelihood of declaring a STEM major was moderated by the effect of having ADHD.

Chapter Four: Influence of Multiple Forms of Capital on STEM Major Intentions for Students with Disabilities

In my fourth chapter, I explored the structural influences on high school students' intentions to declare STEM-related majors upon enrollment in college. I drew from human, cultural, and social capital theories to guide my analysis. These three theories were core components of Perna's (2006) well-known model of college choice. This model was originally intended to study student decision-making around college choice,

not for decision-making around choosing majors. However, the structural components of this model and the attention given to the role of context made the approach of the model attractive for my analysis. Through a review of literature pertaining to the college choice model and major declaration and a review of the STEM-related structural items in HSL:09, I created a revised conceptual framework to test with my outcome of interest.

My revised framework only contained the two innermost layers of Perna's (2006) four-layer model. These two layers captured the contexts I was interested in investigating. Data limitations such as lack of relevant variables for layers three and four and a small analytic sample size reinforced this decision. The innermost layer incorporated the three sources of capital, while the outer layer contained characteristics of the schools that students attended. Because of the nested nature of these layers, my initial analytic approach utilized hierarchical generalized linear modeling (HGLM). However, after examining the diagnostic criteria, I decided that HGLM was unnecessary and instead turned to using logistic regression to model my outcome.

Comparisons of different sources of capital demonstrated significant differences for students across disability types. Students and their parents reported lower educational expectations across most disability types, measures conceptualized as forms of cultural capital. Differences on social capital measures highlighted that students with ADHD in particular participated in fewer STEM-related activities with other students and held less positive feelings about their math teachers than their peers without ADHD. In terms of academic preparation, a component of human capital, identified differences existed across all disability types except for sensory impairments. For instance, students with learning, mobility, ADHD, and/or developmental disabilities earned fewer non-AP

STEM credits in high school and scored lower on the mathematics proficiency exam administered by the NCES, on average.

My revised model did not contain any of the school characteristic variables, which was not surprising given the model diagnostic results from my attempt to utilize a HGLM approach. The final model contained measures of cultural (parental educational expectations and having at least one parent who majored in a STEM field), social (feelings toward math teacher), and human (number of non-AP STEM credits earned) capital. Notably, students with ADHD were more likely to intend to declare a STEM-related major when everything else in the model was controlled (i.e., values were zero). Students with disabilities whose parents held higher than average educational expectations for them and/or who earned higher average non-AP STEM credits in high school were more likely to intend to pursue STEM majors in college. Finally, an interaction effect between having ADHD and being a woman was included, raising questions for future research.

Connected Takeaways and Implications

In this section, I highlight the main takeaways from Chapters Two through Four. Above, brief summaries of each of these chapters were provided. Within each of those chapters, specific takeaways were offered concerning each analysis; however, taken together, these analyses provide deeper insight into my overarching question about the influences on STEM major intentions for students with disabilities. Each of the following takeaways span multiple chapters, derived from results, implications, or both.

Takeaway One: Disability Measurement in National Surveys is Problematic

Chapter Two focused on assessing the definitions used by the NCES in the HSLS:09 as well as the ways disability was measured. This assessment unveiled a number of measurement issues ultimately limiting the ways I was able to use the data in Chapters Three and Four. One of the main issues stemmed from using parents as proxies for capturing disability identification. Instead of asking students to self-identify as experiencing any of several different impairments, these questions were included on the parent survey during the base-year of data collection.

Aside from disenfranchising students by removing their ability to self-identify, this proxy reporting resulted in a large amount of missing data across the disability measures due to a high parental nonresponse rate. In Chapters Three and Four, I imputed missing data; however, I chose to exclude from my analyses all students whose parents did not respond to the survey. Driving the decision was the rest of the imputation model, containing only data from the student surveys. I did not want to impute parental data using student data. Dropping the students whose parents were nonrespondents resulted in close to half of my analytic sample being removed. Immediately, this sample size reduction had implications for the amount of power to conduct my analyses and potentially the representativeness of my analytic samples.

Parents were only asked about impairments experienced by their children during the base-year of data collection. By doing this, the NCES implied that disability is a static identity, which is problematic considering recent research showing great fluctuation in disability identification during college (Bittinger & Acquino, 2017). In the upcoming data release containing the third full wave of data collection, the NCES opted to allow

students to self-identify their disability status. While this change is a move in the right direction by capturing this information directly and returning some power to these students, the disability measures will be challenging to use in any longitudinal analyses. The self-identification and proxy report data cannot be used interchangeably; there is no way to know whether students would have identified the same way their parents identified them if students were asked initially.

An additional challenge when identifying impairment groups to include in the models in Chapters Three and Four was a conceptual overlap between forms of impairment included on the parental survey. Developmental delay was included as one of the types of impairment, which is considered an umbrella term for numerous other forms of impairment (Centers for Disease Control and Prevention, 2015). Several types of impairment that fall under this umbrella term were also asked about on the survey. This conceptual overlap created a challenge around using multiple disability identity categories. Not only was sample size a concern, but I was worried about the validity of responses to the student experiencing any of the impairment types which fell under the umbrella of developmental delay. I avoided aggregating disability types; small subpopulation sizes for students with autism and intellectual disabilities prompted my exclusion of these students from my analytic sample. This ultimately resulted in a loss of 10 students from my sample. While I opted to not combine multiple identities, other approaches that could be followed would be to create groupings around visibility of the disability or neurodiversity.

The HSLs:09 is not the only national education survey which faces measurement problems. Other surveys ask about disability in similarly limited ways. Measurement

decisions made during the survey design phase likely lack input from disability research experts. More work is needed in this area to determine the extent of the problem. The measurement issues I highlighted here significantly impacted analysis decisions for my studies; however, such acknowledgements are seldom found in journal articles. At face value, this may signal to others that these measurement issues are not present. The absence of measurement discussions may be a result of insignificant attention devoted by researchers or limited space available to discuss the issues thoroughly in journal articles. No matter the reason, investigating and understanding these issues are critical for researchers before embarking on projects examining students with disabilities.

Takeaway Two: Benefits of Using Multiple Disability Identity Categories

While using multiple disability identity categories in my analyses was challenging because of the previously mentioned measurement issues, there were several noteworthy benefits. Prior to running my logistic regression models in Chapters Three and Four using the five disability identity categories, I ran the models using only a binary indicator of disability. The results of these models suggested that disability was not a significant predictor of intentions to declare STEM majors upon college enrollment for high school students. However, once I included the categories, my final models produced results showing statistically significant results for different disability types. The results of my analyses highlighted the need to pursue questions around access to college for students with disabilities utilizing disaggregation and multiple data sources. Lee's (2011) findings suggested that there was no difference in the rate at which students with and without disabilities were declaring STEM majors; however, I concluded that there are differences across disability types that warrant additional research.

Additionally, I was able to investigate differences on my calculated factor scales for the expectancy-value framework in Chapter Three and types of capital in Chapter Four across disability categories. Rarely did these results show similar patterns across disability types. These results really spoke to the different experiences of students with disabilities, as opposed to a shared experience by anyone with any type of impairment. A range of experiences should be expected when we step back and think about how this heterogeneous group of students with different impairments engage with STEM-related classes and material. For instance, students with mobility impairments may be limited in the amount of field work they are able to engage in or even have challenges using high lab tables (Brigham, Scruggs, & Mastropieri, 2011; Mastropieri et al., 2006). On the other hand, a student with autism may be particularly drawn to the rigid, rule-based scientific method. The differences are apparent and incorporating more than a single dichotomous indicator acknowledges this, yet including disability identity in ways which allow for fine-grained quantitative analysis can be challenging.

Disability is a diverse identity characteristic, despite its common absence in discussions of diversity on college campuses (Davis, 2011; Olkin, 2002). As higher education moves forward toward a more nuanced view of diversity, disability must not be forgotten. Historically, having a disability has served a role in justifying exclusion of individuals (Reid & Knight, 2006; Siebers, 2008). Instead, higher education should take note of the benefits that students with disabilities bring to college campuses (e.g., Eden, 2017). These students often bring unique views and experiences that have emerged from living life in ways that are different from hegemonic views of normality. Higher education institutions need to embrace the multifaceted nature of disability (Kim &

Acquino, 2017; Kimball et al., 2016), taking steps to attract and support these students along their journeys of educational attainment. Further, as stated previously, disability identity is context dependent. Institutions need to continue taking steps toward creating spaces and experiences where students' disability identity does not even come into play.

Takeaway Three: Benefit of Including Interaction Effects

I included interaction effects in my models in Chapters Three and Four to detect possible moderation of the impact of variables of interest on the likelihood of students with disabilities intending to declare STEM majors. In Chapter Three, these variables were the subjective task value factor scales, while in Chapter Four they were different sources of capital. For both models, I also explored the inclusion of interaction terms between disability identity and being a woman or racial minority. These latter interaction terms were meant to explore the ways that experiencing different types of limitations interfaced with other identities that are underrepresented in STEM fields.

In Chapter Three, I included two interaction terms. The first involved the science intrinsic value for students with mobility impairments, retained in the model because it enhanced the model fit. However, even though the interaction term bettered the fit of the model, it was not a significant predictor of STEM declaration intentions. I was not able to conclude that the impact of science intrinsic value on my outcome differed for students based on their mobility impairment identification, perhaps due to the small subsample of students with such impairments included in my analytic sample. The increased model fit indicated that failing to include this variable would result in omitted variable bias, so retaining the term helped to reduce error in the prediction equation.

The second interaction term was between women and students with ADHD. This same term was also included in Chapter Four. In Chapter Three, this term was found to be a significant predictor of STEM major declaration intentions. When included in the model in Chapter Three, this interaction term led to the ADHD indicator becoming a significant predictor. ADHD indicators resulted in odds ratios considerably over one while the woman indicators resulted in odds ratios substantially under one. Introducing the interaction terms served to acknowledge that women's intentions of pursuing STEM majors varied based on experiencing ADHD. Given that men are more likely to be diagnosed with ADHD (Bruchmüller, Margraf, & Schneider, 2012), this result was a little surprising. Comparatively, women with ADHD were more likely than women without ADHD to intend to declare STEM majors.

Takeaway Four: Students with ADHD More Likely to Pursue STEM

Across both models in Chapters Three and Four, the interaction effect between being a woman and having ADHD improved model fit; however, only the interaction effect in Chapter Three was statistically significant in the final model. Results from Chapter Three indicated that men with ADHD were more likely than students who were White and had average scores for the expectancy-value measures to declare a STEM-related major upon enrolling in college. While this finding did not reoccur in Chapter Four, the interaction effect did improve model fit. Women tended to be less inclined to pursue STEM degrees overall, but also having ADHD seemed to mitigate the disinterest in these degrees.

The finding that students with ADHD were more likely to pursue STEM majors as they entered college aligns with previous research demonstrating the students with an

autism spectrum disorder are more likely to pursue STEM fields (Wei, et al., 2013; 2016). ADHD and autism spectrum disorder are seen as forms of neurodiversity and the inclination towards STEM may be related to this linkage. In the HSLs:09, a small number of students (190) experienced an autism spectrum disorder, a number that further reduced after applying my sample restrictions. My decision to not combine the autism and intellectual disability categories in an attempt to retain these students in the model was driven by the desire for results for each form of disability to be clear. Combinations run the risk of muddying which disability type was driving significant relationships. However, I considered approaching categorization on the basis of neurodiversity, where ADHD and autism spectrum disorder would have been combined. Additionally, specific learning disability would have been included because this type of disability has also been identified as a form of neurodiversity. The relatively large sample sizes of students with ADHD and specific learning disabilities would likely have masked the influence of autism. Considering that students with learning disabilities were not found to be any more or less likely to pursue STEM degrees, results from combinations based on neurodiversity may have resulted in nonsignificant results or reduced influence.

Next Steps for Disability Research

In this section, I reflect back on the findings and implications from my three chapters and suggest next steps for my own research agenda as well as future researchers.

Next Step One: Expand Disability Definition Critique

In Chapter Two, I critically evaluated the definitions used by the NCES to measure disability in the HSLs:09. This focus on the HSLs:09 should not be misconstrued as suggesting that this instrument is the only one in need of improvement.

Critiquing the HSLs:09 was partly due to the fact that I would be using the dataset for the analyses found in Chapters Three and Four and also because of the robustness of this NCEs study in terms of disability measurement. The designers of HSLs:09 should be commended for attempting to measure disability through multiple definitions.

Additionally, the next wave of data contains self-identification of disability as students move through postsecondary education. As a result, I will be well poised to compare rates of proxy reporting of disability and eventual self-identification, providing additional insight into the use of proxies to measure disability.

While the critique of HSLs:09 served as a fruitful endeavor, disability is defined in multiple ways across national surveys. Even within the surveys administered by the NCEs, the definitions employed change as do the types of disability included. The critique embedded in this dissertation needs to be expanded to include additional surveys sponsored by the NCEs as well as other national surveys used in higher education such as the National Survey of Student Engagement and the Freshman Survey administered by the Higher Education Research Institute. By carefully considering the multiple ways disability is currently being defined in higher education research and presenting those definitions in a single, digestible format, disability researchers will be able to argue for the need of common definitions. Such work may be able to serve as the basis for grant funding requests to create standardized definitions to measure disability in education, similar to the work that was completed by the World Health Organization (2001; 2011) in creating the International Classification of Functioning, Disability, and Health.

Next Step Two: National Discussion about Disability Measurement

Unfortunately, working to create a common definition across national surveys is not enough to ensure valid and reliable data for secondary data analysts working to study and improve educational outcomes for students with disabilities. The development of a common definition must also take measurement issues into consideration. For instance, institutions wishing to measure disability on their campuses and compare to national rates should be able to emulate approaches taken in national surveys. Standardized definitions must be measurable in fairly concise ways and be applicable to a wide array of educational situations. If this is accomplished, a trend of including these disability-related questions along with other commonly asked demographic questions capturing components of individuals' identities may emerge.

Reaching a consensus on definitions of disability is a critical first step that needs to be followed by discussions around measurement which bring a variety of stakeholders to the table. If disability researchers want to reach a wide audience, there is a need to understand what kind of information is needed in order to enact change. This audience likely includes other scholars, staff of disability services offices on college campuses, high school staff assisting with transition, and policymakers from the local up to the federal levels. These conversations must also consider the best way(s) to capture disability-related data, calling for the inclusion of survey research experts in these conversations. As discussed in Chapter Two, attempting to capture disability through the use of proxies is problematic. Instead, the discussion around measurement can push for the empowerment of students themselves to identify as experiencing different impairments.

Next Step Three: Model Psychological and Structural Components Together

In Chapters Three and Four, I modeled psychological and structural influences on intention to declare STEM majors upon college enrollment separately. Despite this, a few variables were included in both models: a) gender, b) race, c) disability type, and d) math proficiency. Results for gender and race were consistent across the two models. When everything else in the model was controlled for, women were less likely than men to intend to declare a STEM-related major, and underrepresented racial minority students were just as likely as Asian and White students to intend to declare a STEM major. Students with ADHD were also more likely to intend to declare a STEM major than reference groups in the model.

The similar results across models was promising, and the logical next step would be to combine all measures into a single model to acknowledge the importance of both psychological and structural components, akin to bio-psycho-social models of disability utilized by the World Health Organization (2001). During analysis, several measures were approaching significance and may become statistically significant predictors in a combined model by pushing the test statistics over the arbitrary thresholds. In other words, a combined model may reveal that important influences on STEM major declaration were being hidden due to the omission of other variables.

However, constructing a single psycho-social model was not feasible for my analyses due to sample size concerns. I wanted to include disability as more than a single binary indicator, opting to include multiple indicators of having different impairments. Some of the resulting groups were small, and presented restrictions for the size of my models. Attempting to combine these models with the HSLS:09 would likely require

researchers to combine impairment categories such as sensory and mobility in order to avoid power issues.

Neither the expectancy-value nor sources of capital model worked very well for predicting STEM major intentions of students with disabilities. Therefore, future researchers are not encouraged to utilize these models for their own research on disability, particularly if they intend to also use the HSLs:09. Exploring the utility of these models with other data and other combinations of disability identities is worthwhile to further test whether these models can be useful when studying students with disabilities. A new disability-specific model may need to be specified that includes different emphases that impact students with disabilities in particular or that encompasses concepts from several models such as combining both of the theoretical models I explored.

Next Step Four: Repeat Models with Data from Two Time Points Simultaneously

The models that I fit in this dissertation drew on data from the base-year and first follow-up of data collection for the HSLs:09 separately. During the base year, students were in ninth grade, early on in their high school careers. The first follow-up occurred two years later when students were in eleventh grade. In general, research has demonstrated the relative stability of student career aspirations through high school and beyond (e.g., Maltese & Tai, 2011; Syed, Azmitia, & Cooper, 2011; Tai, Liu, Maltese, & Fan, 2006). While such results provided justification for my modeling approach, these studies often do not consider the role that disability may play in maintaining or disrupting this stability. Disability is an important consideration here due in part to the power that individualized education program (IEP) teams have in determining the classes that

students take during high school, ultimately impacting their college and career aspirations.

IEP teams are meant to help high school students transition from secondary education into the next phase of their life. In theory, these teams aid college-aspiring students in preparing for and ultimately transitioning into postsecondary education; however, college enrollment rates for students with disabilities still lag behind their peers without disabilities (Barber, 2012; Hudson, 2013). Despite being mandated to become involved in the planning process with these teams (Hendricks & Wehman, 2009; Landmark, Ju, & Zhang, 2010), students with disabilities are not always active participants unless provided with explicit instructions about how to engage in the process (Griffin, Taylor, Urbano, & Hodapp, 2014; Test, Mason, Hughes, Konrad, Neale, & Wood, 2004; Wehmeyer, Palmer, Soukup, Garner, & Lawrence, 2007). As a result, the teams are left with making decisions impacting high school course trajectories and, subsequently, future career and educational plans.

Limited research has suggested that these teams may not be working to meet the aspirations laid out by students. One study focusing on transition plans found that the vast majority of students, 77 percent, wanted to pursue a college degree during tenth grade (Hitchings, Retish, & Horvath, 2005). Yet, by the time these students graduated, only 47 percent were still interested in pursuing a college degree and almost none, 4 percent, had a transition plan that would have adequately prepared them for pursuing postsecondary education. Expanding my analyses to consider the first two waves of data collection concurrently could shed more light on the potential impact of these teams in tempering aspirations for students with disabilities. Because of past research demonstrating the

stability of aspirations, models using either wave of data should produce similar results. However, if results are different, this could be an indication of an underlying problem that needs to be investigated.

Conclusion

Moving forward, secondary and postsecondary education professionals have work to do to increase the representation of students with disabilities in STEM fields. Addressing this underrepresentation is not a task that either side should take on alone; instead, by working in conjunction, more fruitful solutions can be developed and student transitions will be more successful. Through my work in this dissertation, I hope to draw attention to disability definition and measurement issues that pose a significant threat to researchers engaging in work to enhance outcomes for students with disabilities. I tested two theoretical models that have been commonly used within education research, neither of which had been utilized in broad disability-related research previously. While neither model was a perfect fit for predicting the STEM majoring intentions of students with disabilities as they enroll in college, meaningful results were obtained that stand a chance at influencing necessary changes and future research efforts in order to facilitate the increased representation of students with disabilities in STEM-related majors and careers.

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