# Development of STEM Readiness Benchmarks to Assist Educational and Career Decision Making 



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#### Abstract

Although about 40\% of high school graduates who take the ACT® test express interest in pursuing a career in a science, technology, engineering, and mathematics (STEM) field, the percentage of firstyear students in college who declare a STEM major is substantially lower. The pool of prospective STEM workers shrinks further as the majority of STEM majors do not earn a STEM degree. A lack of academic preparation in science and mathematics has been offered as one explanation for the leaky STEM pipeline. The purpose of this research was to develop STEM readiness benchmarks to provide prospective students more tailored information on the level of knowledge and skills needed to have a reasonable chance of success in first-year STEM courses. The research had three components.

Study 1 identified the mathematics and science courses that STEM majors take most often in the first year of college. In mathematics, the most prevalent course was Calculus. In science, multiple courses were identified as typically taken by STEM majors: Biology, Chemistry, Engineering, and Physics.

Study 2 derived empirically based STEM readiness benchmarks in mathematics and science by estimating the ACT Mathematics and Science test scores associated with a $50 \%$ probability of earning a grade of a B or higher in the identified STEM courses. Specifically, the median ACT Mathematics score associated with a $50 \%$ probability of earning a B or higher grade in Calculus is 27. The median ACT Science score associated with a $50 \%$ probability of earning a B or higher grade in Chemistry, Biology, Physics, or Engineering is 25.

Study 3 validated the STEM readiness benchmarks on more distal indicators of success. Results demonstrated that STEM majors who met the STEM readiness benchmarks were more likely to earn a cumulative grade point average of 3.0 or higher, persist in a STEM major, and earn a STEM-related bachelor's degree. Providing STEM readiness information to prospective students may help facilitate the transition to college by aligning students' expectations with course demands.


## Introduction

The ability of the United States to maintain a supply of science, technology, engineering, and mathematics (STEM) graduates sufficient to retain its competitiveness in the global economy has come under scrutiny (Langdon, McKittick, Beede, Khan, \& Doms, 2014; National Academy of Sciences, National Academy of Engineering, \& Institute of Medicine, 2005; Obama, 2009; U.S. Department of Labor, 2007). After World War II, the United States led the world in educational achievement, but today the situation is quite different, according to a recent report by the National Science Board (NSB; 2014). Whereas in 2000 the United States produced nearly twice as many graduates with degrees in the physical or biological sciences as did China, in 2010 China produced more than twice as many graduates in these fields as did the United States. In 2010, China, India, Russia, Ukraine, and Japan all produced more engineering graduates than did the United States, and both South Korea and Mexico each produced nearly as many engineers as did the United States. Overall, of the 5.5 million science and engineering degrees awarded throughout the world in 2010, 2.5 million were awarded in Asia, 1.5 million were awarded in Europe, and 0.5 million were awarded in the United States.

Given the importance of the STEM workforce in the modern global economy (Langdon, et al., 2014; U.S. Department of Labor, 2007), there have been calls for producing one million more STEM majors over the next decade (Executive Office of the President, President's Council of Advisors on Science and Technology, 2012). However, research indicates that students leave the STEM pipeline at various transition points along their education career. For example, recent findings indicate that about $40 \%$ of high school graduates who take the ACT ${ }^{\circledR}$ test express interest in majoring in STEM (ACT, 2014b). However, the percentage of students who actually declare a STEM major upon enrollment is substantially lower: in the 1995-1996 academic year, only 17\% of undergraduates declared a STEM major in the first year (Chen, 2009). Based on the same cohort of students, results indicate that only a small percentage of students move into STEM after the first year, with an additional 6\% of undergraduates declaring a STEM major after their first year (Chen, 2009). The pool of prospective STEM workers continues to shrink as the majority of STEM majors do not earn degrees in STEM fields. Only 37\% of first-year STEM majors earned a degree or certificate within six years. Data on a more recent cohort paints a similar picture (Chen, 2013; Chen \& Ho, 2012). The STEM pipeline continues to be leaky as STEM graduates decide on post-baccalaureate pursuits with only a little over half (56\%) obtaining employment in a STEM occupation after graduation (Carnevale, Smith, \& Melton, 2011). ${ }^{1}$

To address this issue, the United States must seek ways to maintain the STEM pipeline with students who are likely to succeed in a STEM major and persist in a STEM field. To this end, we developed STEM readiness benchmarks to help identify students who have a high probability of succeeding in the first-year mathematics and science courses typically taken by STEM majors.

[^0]The STEM readiness benchmarks will also provide a clear signal to students regarding the rigorous demands of the majority of STEM-related coursework. Research shows that many science majors have unrealistic expectations about how they will perform in science courses, contributing to an overly optimistic view of earning a science degree (Stinebrickner \& Stinebrickner, 2014). Many students aspire to enter a STEM field, but they are not academically prepared to do so (Noeth, Cruce, \& Harmston, 2003). For example, of students who completed a core curriculum and intended to major in mathematics, less than a third had at least a $50 \%$ probability of earning a grade of B or higher in a college Calculus class (ACT, 2002). The results for intended science majors revealed that the percentage ready for a college-level Chemistry class was higher but was less than half (47\%).

Providing students with an indicator of their STEM readiness has at least two practical benefits. First, if provided early enough, students who are interested in STEM but not on track to be ready for STEM coursework can take preemptive action to increase the skills and knowledge necessary to be STEM-ready. Second, for students making the transition to college, this information may pique interest among those who are academically ready for STEM but had not previously considered it as a possible major, potentially bolstering the STEM pipeline. By helping students select a major for which they are adequately prepared, much of the frustration associated with selecting and enrolling in coursework that is a poor academic fit, along with the potential downstream negative consequences (e.g., dropping out, switching majors), may be avoided (e.g., Chen \& Ho, 2012; Shaw \& Barbuti, 2010). The goal of this research aligns with the larger objective of the current standards-based educational reform movement in the United States, specifically that of the Common Core State Standards (CCSS): to clearly articulate the knowledge and skills students need to be ready for college and the workforce.

## College and Career Readiness

Students who graduate from high school ill-prepared for the demands of college-level work have been a concern of the United States for decades. Over thirty years ago, the National Commission on Excellence in Education released the report A Nation at Risk, which delineated issues and concerns with the American education system, namely the diluting of standards, which has had the detrimental effect of leaving many students ill-prepared for college-level work and ill-equipped to contribute to the economic health of the country (Gardner, Larsen, Baker, \& Campbell, 1983). The Commission offered several recommendations, one of which was the need to increase the rigor of high school graduation requirements. At a minimum, they indicated that all students should be required to complete four years of English; three years each of mathematics, science, and social studies; and half a year of computer science.

The report served as a call to action; however, the United States seems to be in a similar predicament today with many students earning a high school diploma but lacking the skills and knowledge necessary for college-level coursework. The percentage of students requiring remediation upon entering college illustrates this point. In the 2007-2008 school year, roughly 20\% of all first-year undergraduate students took remedial courses in their first year; the rate was even higher (24\%) among students attending two-year public institutions (U.S. Department of Education, 2013). Corroborating the results of remedial course taking, a survey of college instructors asked to rate the quality of preparation of today's high school graduates indicated that only a quarter of college instructors rated the students they teach as "Well" or "Very Well" prepared for college-level work (ACT, 2013a).

The research clearly indicates a disconnect between the academic skills required for college and work and students' actual levels of preparation. In response, various college and career readiness benchmarks beyond simply earning a high school diploma have been developed to evaluate and track progress toward increasing college and career readiness. One of the earliest examples can be traced back to the National Center for Education Statistics (NCES; Berkner \& Chavez, 1997). A college qualification index was developed that included five levels of readiness based on the distribution of high school grade point average (HSGPA), class rank, National Education Longitudinal Survey (NELS) scores, ACT/SAT scores, and academic coursework among four-year college students. The five levels-very highly qualified, highly qualified, somewhat qualified, minimally qualified, and marginally or not qualified-corresponded to the performance of four-year college students scoring in the top $10 \%, 25 \%, 50 \%, 75 \%$, and the bottom $25 \%$ of each of these measures, respectively. For example, the cut scores or benchmarks for the very highly qualified category were 3.7 for HSGPA, 96th percentile for class rank, 97th percentile on NELS, and an ACT score of 28 or SAT score of 1250. Students only had to achieve one of the criteria (e.g., HSGPA $\geq 3.7$ ) to be classified into that level (e.g., very highly qualified). Based on this classification system, $64.5 \%$ of the 1992 high school graduates were at least minimally qualified, but only $21.4 \%$ were deemed very highly qualified.

The Manhattan Institute for Policy Research also examined college readiness rates using a different set of criteria and model for classification (Greene \& Winters, 2005). Students were considered ready for college if they had earned a high school diploma; completed a minimum set of course requirements-four years of English, three years of math, and two years each of natural science, social science, and foreign language; and could read at a basic level or above on the National Assessment of Educational Progress (NAEP) reading assessment. Unlike the NCES model where classification was based on meeting at least one cut score, college readiness was based on a conjunctive model where students had to meet all three criteria to be considered college ready. Given this distinction, it is not surprising that they concluded that a much smaller percent of students were ready for college, just 34\%. Both of the definitions of college readiness described above set benchmarks irrespective of their relationship with actual college performance. Therefore, whether students who were deemed "college-ready" were actually successful once in college and, alternatively, whether students deemed not ready were actually unsuccessful remained unanswered. To ensure that college readiness indicators were indicative of future college success, others have approached the issue by developing college-readiness benchmarks based on empirically derived predictive relationships.

In 2004, a report by ACT, Crisis at the Core: Preparing All Students for College and Work, again illustrated that the majority of high school graduates were not ready for college-level work; as a result of this analysis, ACT developed empirically derived benchmarks to identify students who had a high likelihood of being successful once in college based on their performance on the ACT (ACT, 2004; Allen, 2013; Allen \& Sconing, 2005). Rooting itself in a content validation framework, ACT derived subject-specific benchmarks by estimating the ACT subject score associated with a $50 \%$ probability of earning a grade of $B$ or higher in a typical credit-bearing first-year course completed by students in the respective subject. For example, the ACT College Readiness Benchmark for Mathematics of 22 was derived based on the relationship between ACT Mathematics scores and course grades in College Algebra; for the ACT English, Science, and Reading tests, the courses
examined were English Composition, Biology, and social science courses, respectively. ${ }^{2}$ Additional research on the relationship between the ACT College Readiness Benchmarks and college success support the value of these benchmarks: students who meet the ACT benchmarks have higher firstyear grade point averages (FYGPAs) and are more likely to persist to the second year and, ultimately, to graduate from college (e.g., ACT, 2010; Radunzel \& Noble, 2012). Among the 2013 ACT-tested cohort, roughly one in four (26\%) met all four of the ACT College Readiness Benchmarks (ACT, 2013b).

In 2007, the College Board released benchmarks specific to the SAT (Kobrin, 2007). Like ACT, the College Board calculated its college readiness benchmark based on the relationship between SAT scores and performance in the first year of college, though there were slight differences. For example, the College Board conceptualized success as earning a FYGPA of a B- or higher whereas ACT examined specific content-related course grades. The College Board also employed a probability level of 65\%; ACT's was $50 \%$. Using SAT composite score (SAT Math + Critical Reading + Writing), ${ }^{3}$ the College Board derived a college readiness benchmark of 1550 (Wyatt, Kobrin, Wiley, Camara, \& Proestler, 2011). Similar to the ACT results, data support the use of the College Board's college readiness benchmark in that students who meet the benchmark are more successful in college, not only in terms of earning higher FYGPAs but also because they are more likely to enroll in college, return for their second year, and graduate in both four and six years (College Board, 2012; Kobrin, 2007; Mattern, Shaw, \& Marini, 2013; Wyatt et al., 2011).

The advent of the CCSS and the resulting formation of two multistate consortia, the Partnership for Assessment of Readiness for College and Careers (PARCC) and Smarter Balanced, have reinvigorated the conversation around college and career readiness (CCSS, 2010). Specifically, the two consortia have developed new assessments that will be aligned to the CCSS. The ultimate goal is to use the new assessments to evaluate college and career readiness of high school students as well as provide diagnostic information at earlier grades regarding whether students are on track for college and career readiness; however, the methodology that the two consortia will use to develop college and career readiness benchmarks for these new assessments has yet to be determined (Camara, 2013; Smarter Balanced Assessment Consortia, 2012). In 2014, ACT launched ACT Aspire ${ }^{\circledR}$, which assesses students' mastery of math, English language arts (ELA), and science in grades 3 through 10, allowing for early monitoring of students' academic strengths and weakness. The ACT College and Career Readiness Benchmarks have been backmapped to ACT Aspire, ${ }^{4}$ allowing for the articulation of what students need to know and be able and willing to do at key transition points along the K-Career continuum. Such information helps students and teachers know if a student is on track for college and career readiness.

[^1]
## College Readiness is Not STEM Readiness

The ACT College Readiness Benchmarks provide useful information regarding the extent to which students are on track for college and career readiness in a general sense, but they do not address (nor were they developed to address) a student's readiness for a specific college major or career field. Research clearly shows that students take different courses in college, and this is due in part to varying course requirements across different majors (Berry \& Sackett, 2009; Goldman, Schmidt, Hewitt, \& Fisher, 1974; Pennock-Roman, 1994; Ramist, Lewis, \& McCamley-Jenkins, 1994; Westrick, 2015a). This is particularly true for STEM majors, which are known for having rigorous course demands and more stringent grading standards (e.g., Goldman et al., 1974; Westrick, 2015a). In fact, the introductory mathematics and science courses for STEM majors are often referred to as "gateway" courses, where students who are not academically suited for STEM majors are less likely to succeed. Research findings clearly indicate that STEM fields require higher levels of mathematics and science knowledge and skills to be successful (Westrick, 2015b); therefore, benchmarks derived on the typical courses students take (e.g., College Algebra) may not serve as an adequate indicator of an individual student's readiness for STEM coursework.

Providing a more precise signal to prospective STEM majors may help with the leaky STEM pipeline in college. Specifically, the majority of STEM attrition occurs in the first year or two, and readiness for college-level STEM coursework is a key factor related to persisting in STEM and ultimately earning a STEM degree (Chang, Cerna, Han, \& Saenz, 2008; Chen, 2013; Seymour \& Hewitt, 1997; Strenta, Elliot, Adair, Matier, \& Scott, 1994). For example, Chen (2013) found that students in their first year who attempted and earned more STEM credits, earned higher grades in their STEM courses, withdrew/failed fewer STEM courses, and took Calculus were more likely to persist in STEM. Taking Calculus in the first year largely differentiated STEM graduates from non-STEM graduates. Of the students who earned a STEM degree, $63 \%$ took Calculus or advanced math in the first year compared to $28 \%$ of students who dropped out of college and $36 \%$ of students who switched to another major. Among biological, biomedical, and behavior science majors, Chang et al. (2008) found that an increase in FYGPA by half a letter grade was associated with roughly a 20\% increase in the likelihood of persisting in one's major. Likewise, Seymour and Hewitt (1997) found that first-year performance was the main determinant of switching out of a STEM major.

Research has clearly demonstrated that high school graduates who are more academically prepared, as measured by high school grades and test scores, are in general more successful in college (ACT, 2010, 2012a, 2013c, 2013d; Radunzel \& Noble, 2012); this is especially true for STEM majors (e.g., Chen 2009, 2013; Kokkelenberg \& Sinha, 2010; Le, Robbins, \& Westrick, 2014; Mendez, Buskirk, Lohr, \& Haag, 2008; Shaw \& Baruti, 2010). In general, research shows that students with higher ACT scores are more likely to return for the second year, earn higher grades, and graduate in a timely manner (ACT, 2010, 2012b, 2013c, 2013d; Radunzel \& Noble, 2012). Research focused on STEM majors has reached similar conclusions. Specifically, students with higher grades and test scores are more likely to express interest in STEM (ACT, 2012a), enroll in a STEM major (e.g., Goldman et al., 1974; Nicholls, Wolfe, Besterfield-Sacre, Shuman, \& Larpkiattaworn, 2007; Le et al., 2014; Pennock-Roman, 1994; Strenta et al., 1994; Westrick, 2015b), earn higher grades in STEM courses (e.g., Chen, 2009, 2013; Chen \& Ho, 2012; Mendez et al., 2008), persist in a STEM major (e.g., Chen, 2009, 2013; Chen \& Ho, 2012; Le et al., 2014; Shaw \& Baruti, 2010), and graduate with a STEM degree (e.g., Chen, 2009; Chen \& Ho, 2012; Kokkelenberg \& Sinha, 2010). For example, Westrick
(2015b) found that among STEM-Quantitative majors who persisted through four years, the average ACT Mathematics score for students earning a GPA of 3.0 or higher by semester was 28 across four years of college. In contrast, for students who earned semester GPAs of less than 3.0, the mean ACT Mathematics score was 24 in the first semester and rose to 26 in the eighth semester (due in part to attrition of lower-scoring students). Of note, both the students who averaged a B or higher and those who averaged less than a B had substantially higher ACT Mathematics scores, on average, than the ACT College Readiness Benchmark in mathematics of 22 , suggesting that a higher benchmark is needed for STEM majors.

In sum, the research clearly indicates that STEM majors who are more academically prepared upon entry into college are more likely to succeed and persist in a STEM field. What remains unknown is the level of academic preparedness students need to have a reasonable chance of succeeding in STEM-related courses; that is the focus of the current study.

## Current Study

The purpose of the current study was to develop indicators or benchmarks of STEM readiness in mathematics and science with the goal of informing students about the level of knowledge and skills needed to succeed in a STEM major. To accomplish this, three studies were conducted. Given that the majority of STEM attrition occurs in the first year or two of college and that it is largely a function of performance in the first-year mathematics and sciences courses, the goal of Study 1 was to determine the typical first mathematics and science courses that STEM majors take or are required to take in their first year of college. Building on Study 1, Study 2 empirically derived STEM readiness benchmarks in mathematics and science based on the relationship between ACT scores and performance in those STEM-identified first-year mathematics and science courses. Finally, Study 3 was conducted to examine the validity of the STEM readiness benchmarks in mathematics and science for predicting future success of STEM majors in terms of earning a cumulative GPA of 3.0 or higher, persisting in a STEM major, and graduating with a STEM-related bachelor's degree.

## Study 1: Course Taking Patterns of STEM Majors

## Sample

We collected data on first-year courses at 27 public four-year postsecondary institutions from three states. ${ }^{5}$ Of the 27 institutions, five have highly selective or selective admissions policies. The remaining 22 institutions have traditional, open, or liberal admissions policies. The median average ACT Composite score across institutions was 21.4 (1 st Quartile [Q1] = 20.3; 3rd Quartile [Q3] = 22.5). In terms of student-level data, course transcript data were available for 176,149 students who had enrolled in college as first-time entering students from the 2005 through 2009 freshman cohorts.

Course Content Coding. Partnering institutions provided ACT with course grade data, course title, and course content codes. ${ }^{6}$ For courses that were not assigned a content code by the participating institution, ACT research staff assigned a code based on the course title and description from the
${ }^{5}$ The majority of ACT-tested students with intentions to major in a STEM field initially enrolled in a four-year postsecondary institution after high school ( $74 \%$ ). Therefore, the decision was made to focus on STEM majors at four-year postsecondary institutions.
${ }^{6}$ Course content codes were developed and used to identify similar content-related courses across institutions, e.g., Calculus, College Algebra, etc.
institution's course catalog. We then identified for each student the first mathematics and science courses taken in the first year. Based on this coding, 100,954 students were identified as taking a mathematics course in their first year. Of these students, $3 \%$ took more than one mathematics course in the same semester. Essentially, these students had multiple "first" mathematics courses in college; as such, they were all included in the analyses. For science, 83,403 students were identified as taking a science course. Students were much more likely to take more than one science course in the same semester-30\%. As was the case with the mathematics results, all of the students' "first" science courses were included in the analyses.

Coding STEM Majors. Institutions also provided students' declared majors over time by reporting a six-digit Classification of Instruction Program (CIP) code for each term enrolled. The first-year CIP codes were used to identify students who declared a STEM major in their first year. Many definitions of STEM exist; the current study used ACT's definition of STEM (2014), which categorized STEM majors into four clusters: Science, Computer Science and Mathematics, Medical and Health, and Engineering and Technology. ${ }^{7}$ Of the 100,954 students who took a mathematics course in their first year, $22 \%$ were classified as a STEM major in both the fall and spring terms of Year 1, which translates to 22,113 students. For science, 23,687 of the 83,403 students who took a science course in their first year were declared STEM majors in both the fall and spring terms of Year 1, which is $28 \%$. Using this information, the most prevalent first mathematics and science course taken in the first year among STEM majors was computed. Characteristics of the students included in the mathematics and science sample are summarized in Tables 1 and 2.

[^2]Table 1. Summary of Student Characteristics of Mathematics Sample for Study 1

| Characteristics | All students ${ }^{\text {a }}$ | Overall STEM | STEM <br> Science | STEM Computer Science and Mathematics | STEM Medical and Health | STEM Engineering and Technology | Non-STEM students |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $N$ (students) | 100,954 | 22,113 | 8,413 | 2,821 | 3,780 | 7,099 | 64,657 |
| Gender |  |  |  |  |  |  |  |
| Female | 52\% | 45\% | 55\% | 27\% | 82\% | 19\% | 55\% |
| Male | 45\% | 53\% | 42\% | 71\% | 16\% | 78\% | 42\% |
| Missing | 2\% | 3\% | 2\% | 2\% | 2\% | 3\% | 2\% |
| Race/Ethnicity |  |  |  |  |  |  |  |
| African American | 14\% | 12\% | 10\% | 18\% | 22\% | 6\% | 14\% |
| Asian American | 3\% | 4\% | 5\% | 3\% | 2\% | 5\% | 2\% |
| Hispanic | 9\% | 12\% | 14\% | 12\% | 5\% | 13\% | 9\% |
| Other | 6\% | 5\% | 5\% | 4\% | 5\% | 4\% | 6\% |
| White | 62\% | 60\% | 59\% | 56\% | 62\% | 63\% | 62\% |
| Missing | 7\% | 7\% | 7\% | 7\% | 5\% | 9\% | 6\% |
| ACT Composite score |  |  |  |  |  |  |  |
| Mean | 21.8 | 23.3 | 23.4 | 22.8 | 20.3 | 25.0 | 21.5 |
| Standard deviation | 4.7 | 4.9 | 4.7 | 5.2 | 4.2 | 4.8 | 4.5 |
| HSGPA |  |  |  |  |  |  |  |
| Mean | 3.40 | 3.55 | 3.60 | 3.41 | 3.36 | 3.64 | 3.38 |
| Standard deviation | 0.53 | 0.48 | 0.43 | 0.57 | 0.53 | 0.41 | 0.52 |
| Missing | 17\% | 15\% | 14\% | 16\% | 13\% | 16\% | 17\% |

[^3]Table 2. Summary of Student Characteristics of Science Sample for Study 1

| Characteristics | All students ${ }^{\text {a }}$ | Overall STEM | STEM <br> Science | STEM Computer Science and Mathematics | STEM Medical and Health | STEM Engineering and Technology | Non-STEM students |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $N$ (students) | 83,403 | 23,687 | 10,140 | 1,708 | 4,370 | 7,469 | 49,053 |
| Gender |  |  |  |  |  |  |  |
| Female | 54\% | 47\% | 56\% | 29\% | 82\% | 19\% | 57\% |
| Male | 44\% | 50\% | 41\% | 69\% | 16\% | 78\% | 40\% |
| Missing | 3\% | 3\% | 3\% | 2\% | 2\% | 3\% | 3\% |
| Race/Ethnicity |  |  |  |  |  |  |  |
| African American | 11\% | 9\% | 9\% | 18\% | 14\% | 5\% | 12\% |
| Asian American | 3\% | 5\% | 6\% | 3\% | 2\% | 5\% | 3\% |
| Hispanic | 8\% | 11\% | 13\% | 12\% | 5\% | 11\% | 8\% |
| Other | 6\% | 5\% | 5\% | 4\% | 5\% | 4\% | 6\% |
| White | 65\% | 63\% | 60\% | 55\% | 70\% | 65\% | 65\% |
| Missing | 7\% | 7\% | 7\% | 8\% | 4\% | 9\% | 7\% |
| ACT Composite score |  |  |  |  |  |  |  |
| Mean | 22.8 | 24.0 | 23.9 | 23.3 | 21.5 | 25.8 | 22.4 |
| Standard deviation | 4.6 | 4.7 | 4.5 | 5.3 | 4.0 | 4.6 | 4.5 |
| HSGPA |  |  |  |  |  |  |  |
| Mean | 3.51 | 3.62 | 3.64 | 3.47 | 3.48 | 3.70 | 3.48 |
| Standard deviation | 0.48 | 0.43 | 0.41 | 0.54 | 0.47 | 0.36 | 0.49 |
| Missing | 16\% | 14\% | 14\% | 17\% | 12\% | 16\% | 16\% |

Note. Percentages may not sum to $100 \%$ due to rounding.
${ }^{\text {a }}$ The number of students in this column is not the sum of the overall STEM column and the non-STEM students column. Students who were STEM majors for only one term in their first year were in the total group but not included in the subanalyses given that they did not cleanly fall into either category.

## Results

The percentage of students who took a mathematics and science course by content area was computed for the total sample and by STEM major category. ${ }^{8}$ Specifically, the most typical first-year mathematics and science course was examined for all STEM majors and for each of the four STEM clusters. This was compared to all students and non-STEM majors. The results for mathematics and science are summarized in Tables 3 and 4, respectively.

Mathematics Results. Across all students in the sample, regardless of their major, College Algebra was the most typical course (28\%). For non-STEM majors, the percentage was slightly higher (31\%). Moreover, an additional $21 \%$ of all students first enrolled in courses below College Algebra; courses often considered developmental, non-credit-bearing courses. These results coincide with the ACT College Readiness Benchmark research that derived the ACT Mathematics Benchmark on course grades in College Algebra (Allen, 2013; Allen \& Sconing, 2005). However, when focusing exclusively on STEM majors, a different pattern emerges. Namely, over a quarter of STEM majors took Calculus I as their first mathematics course (28\%); another 10\% took Calculus II as their first course. Only $11 \%$ of non-STEM majors took Calculus I as their first mathematics courses; for another $2 \%$, it was Calculus II. Clearly, STEM majors are more frequently enrolling in higher-level mathematics courses compared to non-STEM majors.

[^4]Table 3. Distribution (\%) of Students' First College Mathematics Course by STEM Category

| Mathematics content area | All students | Overall STEM | STEM <br> Science | STEM Computer Science and Mathematics | STEM Medical and Health | STEM Engineering and Technology | Non-STEM students |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Business Mathematics | 5 | 3 | 4 | 5 | 3 | 1 | 6 |
| Arithmetic | 1 | 0.3 | 0.3 | 0.4 | 1 | 0 | 1 |
| Elementary Algebra | 8 | 5 | 4 | 7 | 15 | 1 | 9 |
| Intermediate Algebra | 12 | 6 | 7 | 7 | 13 | 2 | 13 |
| College Algebra | 28 | 18 | 22 | 15 | 48 | 5 | 31 |
| Geometry | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Analytical Geometry | 1 | 2 | 3 | 2 | 1 | 0.1 | 1 |
| Trigonometry | 4 | 7 | 9 | 7 | 2 | 7 | 3 |
| Precalculus | 6 | 5 | 6 | 11 | 0.5 | 4 | 6 |
| Calculus I | 15 | 28 | 25 | 28 | 3 | 38 | 11 |
| Statistics | 2 | 2 | 3 | 1 | 3 | 1 | 2 |
| Logic | 3 | 1 | 1 | 5 | 0.4 | 0.3 | 4 |
| Other | 10 | 10 | 8 | 8 | 8 | 13 | 10 |
| Contemporary Mathematics | 2 | 3 | 6 | 1 | 3 | 0.3 | 2 |
| Survey Calculus | 3 | 7 | 3 | 5 | 1 | 13 | 2 |
| Calculus II | 4 | 10 | 6 | 8 | 0.1 | 18 | 2 |
| Multiple courses | 3 | 4 | 5 | 9 | 2 | 3 | 2 |

[^5]Table 4. Distribution (\%) of Students' First College Science Course by STEM Category

| Science content area | All students | Overall STEM | STEM <br> Science | STEM Computer Science and Mathematics | STEM Medical and Health | STEM Engineering and Technology | Non-STEM students |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| General Science | 1 | 0.3 | 0.1 | 2 | 1 | 0.1 | 1 |
| Biology | 34 | 31 | 47 | 26 | 48 | 8 | 35 |
| Chemistry | 35 | 54 | 60 | 25 | 40 | 57 | 24 |
| Physics without Calculus | 2 | 2 | 1 | 3 | 0.4 | 3 | 1 |
| Physics with Calculus | 2 | 4 | 2 | 4 | 0.1 | 8 | 1 |
| Botany | 1 | 1 | 1 | 1 | 0 | 0.1 | 1 |
| Ecology | 1 | 1 | 1 | 0.3 | 0 | 0.2 | 0.5 |
| Engineer | 10 | 23 | 2 | 5 | 1 | 57 | 4 |
| Zoology | 6 | 5 | 10 | 3 | 2 | 0.5 | 6 |
| Anatomy | 2 | 2 | 1 | 1 | 11 | 0 | 2 |
| Health Science | 21 | 13 | 14 | 18 | 38 | 2 | 25 |
| Astronomy | 2 | 1 | 0.5 | 4 | 0.1 | 0.4 | 3 |
| Geology | 7 | 3 | 2 | 10 | 0.3 | 5 | 10 |
| Meteorology | 1 | 1 | 3 | 1 | 0 | 0.1 | 1 |
| Other | 9 | 15 | 7 | 19 | 1 | 27 | 7 |
| Biology II | 0.3 | 1 | 1 | 0.4 | 0.4 | 0.3 | 0.2 |
| Chemistry II | 1 | 1 | 1 | 0.3 | 0.3 | 1 | 0.3 |
| Multiple courses | 30 | 49 | 47 | 19 | 37 | 60 | 20 |

Note. Data are based on 27 public four-year institutions from three states (2005 through 2009 freshman cohorts). There were 83,403 total students, 23,687 first-year STEM majors, and 49,053 first-year non-STEM majors. The breakdown by STEM cluster was: 10,140 for science; 1,708 for computer science and mathematics; 4,370 for medical health; and 7,469 for engineering. Examples of courses included in the "Other" category include Physical Science, Earth Science, and Space Science. Percentages will sum to above 100\% due to the fact that some students took multiple science courses in the same term.

That being said, a sizable percentage of STEM majors first enrolled in lower mathematics courses, including 5\% for Elementary Algebra. Such findings highlight the misalignment between career aspirations and academic preparation for some students and may explain some of the STEM attrition occurring at the postsecondary level. This is supported empirically where research has consistently found that students in developmental courses are less successful in college than their nondevelopmental peers (Noble \& Sawyer, 2013).

The mathematic results were also examined by STEM cluster, and the results largely mirror the overall STEM results with Calculus being the most typical first mathematics course taken for the Science, Computer Science and Mathematics, and Engineering and Technology clusters. ${ }^{9}$ The only cluster that diverged from these findings was the Medical and Health cluster where College Algebra was the most typical first mathematics course taken. Previous research has shown that students interested in these fields tend to be less academically prepared (ACT, 2014b). It should also be pointed out this cluster comprises a small percentage of STEM majors at four-year institutions

[^6]as well as inclusive of majors not typically thought of as traditional STEM majors (e.g., Medical Laboratory Technology; for a complete list of the majors included in this cluster, see ACT, 2014). In the current sample, $70 \%$ of the students in the Medical and Health Cluster were majoring in nursing.

Science Results. Examination of students' first science course indicated that Biology and Chemistry were the most prevalent courses taken across all students (see Table 4). Focusing on non-STEM majors, Biology was more typical (35\%) than Chemistry (24\%). For STEM students, the most typical first science course taken was Chemistry (54\%), followed by Biology (31\%), and Engineering (23\%). Moreover, nearly half (49\%) had more than one "first" science course compared to $20 \%$ of non-STEM students. Disaggregating the results by STEM cluster, Chemistry was the most typical course for the STEM Science cluster, whereas Engineering and Chemistry were equally likely for the STEM Engineering and Technology cluster (57\%). The STEM Engineering and Technology cluster had the largest percentage of students with multiple first science courses (60\%). For the STEM Computer Science and Mathematics cluster, Biology and Chemistry were the most typical courses with $26 \%$ and $25 \%$, respectively. Finally, for the STEM Medical and Health cluster, Biology was the most typical first science course.

Course Requirement Results. To supplement these findings, first-year mathematics and science course requirements of the most popular STEM majors were coded from course catalogs of college and universities that admitted the largest percentages of ACT-tested students who intended on majoring in STEM. ${ }^{10}$ Specifically, the top 10 institutions that enrolled the most ACT-tested students who were planning to major in STEM for each of the four STEM clusters were identified. For the top three to four majors within each cluster, ${ }^{11}$ the first-year course requirements in mathematics and science were coded from the course catalog. Based on a sample of 90 STEM major-by-institution comparisons, $79 \%$ indicated Calculus as a first year requirement. The first-year science requirements varied more as a function of the field of study; however, $90 \%$ indicated Chemistry, Biology, Physics, and/or Engineering as satisfying first-year requirements. These findings coincide with the empirical course-taking results summarized above with the exception of Physics, which was more frequently identified in these supplemental analyses. The findings from both analyses informed the selection of college courses used to derive STEM readiness benchmarks in mathematics and science.

## Study 2: Development of STEM Readiness Benchmarks

## Sample

Course grade data used in the current study were provided by four-year postsecondary institutions that have participated in research services offered by ACT, including state partnerships, the Course Placement Service, and Prediction Service. Data included in the analyses were limited to students from the 2005 through 2009 freshman cohorts. The number of institutions and students per analysis varied based on the data available by course content area; this information along with additional information on key institutional and student characteristics of the sample is summarized in Tables 5 and 6. Similar to Study 1, students' first mathematics and science courses taken during the first year were used in the analyses. ${ }^{12}$

[^7]Table 5. Summary of Institutional Characteristics of Study 2

| Characteristic | Calculus | Combined Science | Population |
| :--- | :---: | :---: | :---: |
| \# of four-year institutions | 37 | 70 | 1,251 |
| Admissions policy |  |  |  |
| Highly selective, selective | $43 \%$ | $26 \%$ | $39 \%$ |
| Traditional, open, liberal | $57 \%$ | $74 \%$ | $61 \%$ |
| Sector |  |  |  |
| $\quad$ Private | $11 \%$ | $29 \%$ | $60 \%$ |
| $\quad$ Public | $89 \%$ | $71 \%$ | $40 \%$ |
| Region | $14 \%$ | $16 \%$ | $47 \%$ |
| $\quad$ East | $22 \%$ | $24 \%$ | $26 \%$ |
| Midwest | $51 \%$ | $46 \%$ | $10 \%$ |
| Southwest | $14 \%$ | $14 \%$ | $16 \%$ |
| West | 22.4 |  |  |
| Average ACT Composite score | 21.5 |  | 22.8 |
| Median | 25.0 | 20.9 to 23.4 | 20.5 to 24.1 |

Note. Combined Science courses include Biology (58 institutions), Chemistry (44 institutions), Physics with Calculus ( 7 institutions), and Engineering ( 6 institutions). Thirty-nine of the institutions had grades available for only one science course; 31 institutions had grades available for more than one science course (three institutions had all four; seven had three courses; 21 had two courses). Population includes four-year postsecondary institutions where 2012 ACT-tested graduates initially enrolled in fall 2012 (determined using enrollment records from the National Student Clearinghouse).

## Analyses

The same methodology employed to derive the ACT College Readiness Benchmarks was used in the current study (Allen \& Sconing, 2005; Allen, 2013). The distinction from the previous research is that the benchmarks were derived based on performance in the STEM-identified mathematics and science courses from Study 1 instead of the most typical course among all students. In mathematics, performance in Calculus was examined. In science, the most common course taken varied by the field of study; therefore, a combination of science courses was examined: Chemistry, Biology, Physics, and Engineering. Course success was defined as earning a grade of a B or higher. To account for students being nested within institutions, hierarchical logistic random intercepts and slopes regression models ${ }^{13}$ were run to estimate the following relationships between scores on the ACT and course success:

- ACT Mathematics scores and success in Calculus.
- ACT Science scores and success in Chemistry, Biology, Physics, and/or Engineering.

[^8]Table 6. Summary of Student Characteristics of Study 2

| Characteristics | Calculus | Combined Science | Population |
| :--- | :---: | :---: | :---: |
| $N$ (students) | 22,246 | 69,328 | $1,168,752$ |
| Gender |  |  |  |
| Female | $43 \%$ | $53 \%$ | $53 \%$ |
| Male | $54 \%$ | $46 \%$ | $47 \%$ |
| Missing | $3 \%$ | $2 \%$ | $0.3 \%$ |
| Race/Ethnicity |  |  |  |
| African American | $3 \%$ | $8 \%$ | $15 \%$ |
| Asian American | $5 \%$ | $4 \%$ | $3 \%$ |
| Hispanic | $6 \%$ | $6 \%$ | $10 \%$ |
| Other | $4 \%$ | $3 \%$ | $4 \%$ |
| White | $74 \%$ | $6 \%$ | $63 \%$ |
| Missing | $8 \%$ |  | $5 \%$ |
| ACT Composite score |  |  |  |
| Mean | 25.5 | 4.3 | 20.7 |
| Standard deviation | 3.8 | 3.60 | 5.1 |
| HSGPA | 0.43 | 3.17 |  |
| Mean | 3.66 | 0.37 |  |
| Standard deviation |  |  |  |

Note. Combined Science courses include Biology ( 29,784 students), Chemistry ( 36,382 students), Physics w/Calculus ( 629 students), or Engineering ( 2,533 students). Population includes ACT-tested high school graduates of 2012 from states where at least 50\% of students took the ACT.

The NLMIXED procedure within SAS 9.2 statistical software was used to fit the models and obtain the parameter estimates for each college.

For Calculus, the estimated intercepts and slopes were used to calculate institution-specific ACT Mathematics scores associated with a $50 \%$ probability of success in Calculus. Data permitting, the estimated intercept and slope derived for each science course (i.e., Chemistry, Biology, Physics, and Engineering) within each institution was used to compute the institution-specific ACT Science score associated with a $50 \%$ probability of success in each science content area. For each institution, the median ACT Science score of the within-institution science results was computed. Finally, after apply institutional weighting, ${ }^{14}$ the median STEM readiness benchmarks in mathematics and science across institutions was computed.

[^9]
## Results

Descriptive results. The distribution of course grades in Calculus and each of the science courses was examined. For Calculus, $53 \%$ of students earned a grade of a B or higher in the course. Across the four science courses examined, roughly half (49\%) of the students earned a B or higher, though it did vary by content area with more students earning a B or higher grade in Physics and Engineering than Chemistry and Biology. Specifically, 69\% of students earned a grade of a B or higher in Physics and Engineering compared to 50\% for Chemistry and 45\% for Biology.

Hierarchical logistic regression results. Calculus results. First-year Calculus grades were available on over 20,000 students attending one of 37 four-year institutions. ${ }^{15}$ The median ACT Mathematics score associated with a $50 \%$ probability of earning a B or higher grade in Calculus is 27 ( $\mathrm{Q} 1=25$; $\mathrm{Q} 3=28$; see Table A1 for parameter estimates). This is consistent with previous research on the relationship between ACT Mathematics scores and Calculus grades (ACT, 2014a). Graphically illustrating the positive relationship between performance on the ACT Mathematics test and grades earned in Calculus courses, Figure 1 highlights that higher ACT Mathematics scores are associated with a higher likelihood of success at typical postsecondary institutions. For example, students who score at the top of the ACT Mathematics score range have an over 80\% probability of earning a grade of $B$ or higher in Calculus. On the other hand, students with an ACT Mathematics score of 22, which is the ACT College Readiness Benchmark, have only a 32\% chance of similar success in Calculus. The probability of earning a C or higher is also plotted. For students with an ACT Mathematics score of 27 or above, students' chances of earning a C or higher is at least $75 \%$ at typical four-year postsecondary institutions.

Combined Science results. Chemistry, Biology, Physics, and Engineering course grade data were available for a larger number of students. ${ }^{16}$ Namely, the analyses for the combined science courses are based on nearly 70,000 students attending one of 70 four-year institutions. The median ACT Science score associated with a 50\% probability of earning a B or higher grade in Chemistry, Biology, Physics, or Engineering is $25(01=24 ; \mathrm{Q} 3=27)$. Figure 2 graphically displays the increasing likelihood of success in one of these science courses as ACT Science scores increase (parameter estimates are provided in Table A1). As was the case with the Calculus results, students who score at the top end of the ACT Science score scale are very likely to be successful in STEMidentified science courses.

The results from Study 2 strongly suggest that higher ACT Mathematics and Science scores are needed for students to have a reasonable chance of being successful in typical first-year subjectrelated courses taken by STEM majors.

[^10]

Figure 1. Probability of Success in Calculus I by ACT Mathematics Score at Typical FourYear Institutions


Figure 2. Probability of Success in Chemistry, Biology, Physics, or Engineering Courses by ACT Science Score at Typical Four-Year Institutions

## Study 3: Validation of STEM Readiness Benchmarks

Study 3 examined whether STEM majors who met the STEM benchmarks were more successful later in college than students who did not. Multiple indicators of later success in college were examined: earning a cumulative GPA of 3.0 or higher in Years 1 through 4, persisting in a STEM major to the second, third, and fourth year, and graduating with a STEM degree in 4, 5, or 6 years.

## Sample

Longitudinal college outcomes data used in the current study were provided by four-year postsecondary institutions who have participated in research services offered by ACT. Data included in the analyses were limited to students who were first-year STEM majors from the 2005 through 2009 cohorts, who were tracked primarily at their initial institution for at least four years. ${ }^{17}$ College outcomes data were available from 48 institutions, representing 53,109 STEM majors. Of these STEM majors, 32\% met the STEM mathematics benchmark and 39\% met the STEM science benchmark. Scores on the ACT Mathematics and Science tests are highly correlated ( $r=0.77$ ); therefore, the percentage meeting both or neither is quite high ( $80 \%$ ) with $55 \%$ meeting neither and $25 \%$ meeting both. Of students who met the STEM mathematics benchmark ( $n=16,932$ ), the majority met the STEM science benchmark (78\%); however, only 65\% of students who met the STEM science benchmark also met the STEM mathematics benchmark. Additional information on key institutional and student characteristics of the sample is summarized in Tables 7 and 8.

[^11]Table 7. Summary of Institutional Characteristics of Study 3

| Characteristic | Study 3 |
| :--- | :---: |
| $N$ (four-year institutions) | 48 |
| Admissions policy |  |
| Highly selective, selective | $25 \%$ |
| Traditional, open, liberal | $75 \%$ |
| Sector |  |
| Private | $27 \%$ |
| Public | $73 \%$ |
| Region | $13 \%$ |
| East | $10 \%$ |
| Midwest | $73 \%$ |
| Southwest | $4 \%$ |
| West |  |

Average ACT Composite score
Median
21.6

1st quartile to 3rd quartile $\quad 20.4$ to 23.3

Note. The typical (median) number of first-year STEM majors per institution was 624 students (ranged from 70 to 4,541 students).

Table 8. Summary of STEM Student Characteristics of Study 3

| Characteristic | Study 3 |
| :--- | :---: |
| $N$ (students) | 53,109 |
| Gender |  |
| Female | $48 \%$ |
| Male | $49 \%$ |
| Missing | $3 \%$ |
| Race/Ethnicity |  |
| African American | $10 \%$ |
| Asian American | $4 \%$ |
| Hispanic | $9 \%$ |
| Other | $5 \%$ |
| White | $64 \%$ |
| Missing | $8 \%$ |
| ACT Mathematics score | $68 \%$ |
| $<27$ | $32 \%$ |
| 27 (met STEM mathematics benchmark) |  |
| ACT Science score | $61 \%$ |
| $<25$ | $39 \%$ |
| $\geq 25$ (met STEM science benchmark) |  |


| Academic performance | Mean (SD) |
| :--- | :--- |
| ACT score |  |
| Composite | $23.7(4.9)$ |
| English | $23.4(5.7)$ |
| Mathematics | $23.8(5.3)$ |
| Reading | $23.8(5.9)$ |
| Science | $23.3(4.8)$ |
| HSGPA |  |
| Overall | $3.56(0.46)$ |
| Math | $3.5(0.6)$ |
| Science | $3.6(0.5)$ |

## Analyses

Due to the nested structure of the data, various hierarchical logistic regression models were used to estimate students' chances of succeeding in a STEM major at typical four-year institutions. To examine cumulative course performance, we used hierarchical logistic regression models to estimate the probability of earning a 3.0 (equivalent to a grade of a B) or higher cumulative GPA at the end of Year 1 through the end of Year 4 as a function of whether the STEM readiness benchmark was met. Parameter estimates for both the intercept and benchmark indicator (met/not met) were allowed to vary randomly across institutions. Analyses of cumulative grades beyond Year 1 were based on the subsample of students who persisted in a STEM major to ensure that a majority of their grades were earned in STEM-related courses. For students who were not enrolled during the second term of their first year, their GPAs from the first term were carried forward and used in the Year 1 cumulative GPA analyses.

For persistence in STEM, a hierarchical multinomial regression model employing a logit link was used to evaluate students' chances of three distinct outcomes: persisting in a STEM major, switching to a non-STEM major, and dropping out of the institution. Persisting in a STEM major was the reference category. For each time point (Year 2 to Year 4), the three-category STEM persistence outcome was based on students' declared majors during the spring semester of the corresponding year. ${ }^{18}$ Students who were no longer enrolled but who had completed a bachelor's degree were categorized as persisting in STEM or switching to non-STEM according to their degree major. Intercepts were allowed to vary randomly across institutions. ${ }^{19}$

Hierarchical discrete-time survival models under the proportional hazards assumption were developed to predict STEM-related bachelor's degree completion from the STEM readiness indicators (Singer \& Willett, 1993; Reardon, Brennan, \& Buka, 2002). This approach simultaneously models all time periods while also accounting for censored observations due to the various freshman cohorts being tracked for different lengths of time. In these models, the logit of the conditional probability of degree completion in a particular term, given that no degree was earned prior to that term, was modeled as a linear function of term indicators and the STEM readiness benchmark indicator. The discrete-time analyses focused on fall and spring terms. There were very few degrees given in the summer terms; summer term degree completion was therefore combined with that for the prior spring term. Term indicators for Term 6 (spring/summer term of Year 3) through Term 12 (spring/summer term of Year 6) were included in the models. Parameter estimates for the term indicators and the STEM readiness indicator were allowed to vary randomly across institutions.

The GLIMMIX procedure for generalized mixed models, available in SAS 9.2, with the Laplace estimation method was used to fit the models. In both mathematics and science, the STEM readiness indicator was a statistically significant predictor for all outcomes across all time points, $p<0.0001$.

[^12]
## Results

Cumulative GPA. Summarized in Table 9, the results indicate that the likelihood of earning a cumulative GPA of 3.0 or higher was strongly related to meeting the STEM benchmarks (see Table A2 for parameter estimates for the models). For students meeting the STEM mathematics benchmark, the chance of earning a cumulative GPA of 3.0 or higher in Year 1 was $71 \%$. Their chances rose to a high of $80 \%$ in Year 4. In contrast, for students not meeting the STEM mathematics benchmark, the chances of earning a cumulative GPA of 3.0 or higher across the four years was much lower, ranging from a low of 39\% for Year 1 to a high of 57\% in Year 4. A similar pattern of results emerged by STEM science benchmark attainment.

Table 9. STEM Students' Estimated Probability of Earning a Cumulative GPA of 3.0 or higher by STEM Benchmark Attainment

|  | Year 1 |  | Year 2 |  | Year 3 |  | Year 4 |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | $N$ | Prob. | $N$ | Prob. | $N$ | Prob. | $N$ | Prob. |
| STEM mathematics benchmark (27) |  |  |  |  |  |  |  |  |
| Not met | 34,291 | . 39 | 18,095 | . 48 | 14,598 | . 53 | 12,991 | . 57 |
| Met | 15,661 | . 71 | 11,495 | . 76 | 10,363 | . 78 | 9,807 | . 80 |
| STEM science benchmark (25) |  |  |  |  |  |  |  |  |
| Not met | 30,995 | . 38 | 16,473 | . 46 | 13,331 | . 51 | 11,882 | . 55 |
| Met | 18,957 | . 64 | 13,117 | . 73 | 11,630 | . 75 | 10,916 | . 77 |

Note. Cumulative GPA for Year 2 and beyond are based only on students who remained in a STEM field. $N=$ sample size;
Prob. $=$ probability.

Persistence in STEM. As was the case for cumulative GPA, students who met the STEM readiness benchmarks were more likely to persist in a STEM major. As displayed in Figure 3, students' chances of persisting in a STEM major to Year 2 was $71 \%$ for those who met the STEM mathematics benchmark compared to $52 \%$ for those who did not met the STEM benchmark (parameter estimates are provided in Table A3). STEM benchmark attainment was also related to students' chances of not being enrolled at the institution at the end of Year 2: $29 \%$ of those who were not STEM ready in mathematics as compared to $17 \%$ for those who were STEM ready in math. Students' likelihood of switching to a non-STEM major by academic year is also provided. In Year 2, the likelihood was 19\% for those who were not STEM ready in mathematics compared to $11 \%$ for those who were STEM ready in math. By Year 4, the chances of students persisting in a STEM major, switching into a nonSTEM major, and no longer being enrolled at that institution were $59 \%, 13 \%$, and $28 \%$, respectively, for those who were STEM ready in math and $36 \%, 21 \%$, and $43 \%$, respectively, for those who were not. A similar pattern emerged when examining persistence rates by STEM science benchmark attainment status. Namely, STEM attrition occurred more frequently for students who did not meet the STEM readiness benchmark in Science.


Figure 3. Probability of Persisting in a STEM Field Compared to Leaving STEM or Being No Longer Enrolled at the Institution by STEM Benchmark Attainment

STEM-related bachelor's degree. Finally, the results indicate that students entering college academically ready for STEM coursework were more likely to earn a STEM-related bachelor's degree compared to STEM majors who did not meet the STEM readiness benchmarks (see Figure 4 and Table A4). By the end of six years, students' chances of earning a STEM-related bachelor's degree was roughly half (49\%) for students who met the STEM mathematics benchmark. In fact, these students were more than twice as likely to earn a STEM-related bachelor's degree than students who did not meet the STEM mathematics benchmark (23\%). For the STEM science benchmark, students' chances of earning a STEM-related bachelor's degree was $42 \%$ for those who met the benchmark and 22\% for those who did not. Additional analyses were run to model students' probability of being successful for the various outcomes if they met both STEM readiness benchmarks, and the results indicated that students who met both were more likely to be successful than students who met only one or neither.


Figure 4. Probability of Completing a STEM-Related Bachelor's Degree in Four, Five, and Six Years by STEM Benchmark Attainment

In sum, the STEM readiness benchmarks not only provide information about students' likelihood of earning a grade of a B or higher in typical first-year mathematics and science courses taken by STEM majors, but they are also related to a variety of important and long-term academic outcomes such as earning a cumulative GPA of 3.0 or higher through the fourth year of college, persisting in a STEM major, and ultimately earning a STEM-related bachelor's degree.

## Discussion

The current study builds on the literature on STEM majors and academic success. Namely, to the best of the authors' knowledge, this is the first study to examine the first-year course-taking patterns of STEM majors using actual course transcript data as well as institution course catalog program requirements. The results clearly indicate that STEM majors are more likely than typical students to take higher-level mathematics courses beyond College Algebra (namely, Calculus) during their first year in college. In science, multiple courses were identified as the typical first-year science course taken by STEM majors, with the most prevalent course tending to vary somewhat by STEM cluster. These courses included Biology, Chemistry, Engineering, and Physics. Based on students' actual course grades, the level of proficiency needed in mathematics and science to ensure a reasonable probability of success (50\% of a B or higher) in their first-year, STEM-related mathematics and science courses was estimated. The results underscore the fact that a higher level of academic preparation is needed than that of the typical college student, as indicated by higher cut scores for the STEM readiness benchmarks than the general ACT College Readiness Benchmarks in mathematics and science. We also evaluated the importance of meeting the STEM readiness benchmarks for success in STEM beyond first-year mathematics and science courses. The findings indicate that meeting the STEM readiness benchmarks is associated with greater chances of earning a cumulative GPA of 3.0 or higher over time, persisting in a STEM major, and earning a STEM-related bachelor's degree.

Providing students with this type of information early on to help them determine whether they are prepared to major in STEM will hopefully result in more students entering the field who are academically ready for its rigorous demands, thereby potentially avoiding the negative consequences associated with enrolling in a program that is a poor academic fit (e.g., switching major). Specifically, the STEM readiness benchmarks can be backmapped to the ACT Aspire score scale, providing the opportunity to give students information on their level of readiness for STEM as early as third grade. Additionally, this information may help spark interest in STEM among those who are academically prepared, potentially bolstering the STEM pipeline.

One limitation of the current study is its exclusive focus on the cognitive determinants of STEM success. Research clearly suggests that performance in school and on the job is jointly influenced by both cognitive and non-cognitive factors (e.g., Allen \& Robbins, 2010; Barrick \& Mount, 1991; Le et al., 2014; Nye, Su, Rounds, \& Drasgow, 2012; Poropat, 2009; Richardson, Abraham, \& Bond, 2012; Robbins, Lauver, Le, Davis, Langley, \& Carlstrom, 2004; Van Iddekinge, Putka, \& Campbell, 2011). Not specific to STEM majors but to all college students, Allen and Robbins (2010) found that motivation (as measured by ACT Engage ${ }^{\circledR}$ ) and interest-major congruence was predictive of timely degree completion above and beyond academic preparation. Examining the role of motivational factors, students' interests in STEM, and their high school coursework and grades in conjunction with test scores to better understand STEM success seems like a fruitful avenue. Though out of the current paper's scope, preliminary analyses were run examining the incremental validity of STEM interests over mathematics and science ability in predicting STEM success. Using the sample of STEM majors from Study 3, the results indicate that expressed interest in STEM (i.e., student's intentions to major in STEM as a high school student) and measured interests in STEM (based on responses to the ACT Interest Inventory [2009], which was initially developed by Holland and based on his theory of vocational interests [1997]) did add incrementally to the prediction of all three measures of success: cumulative GPA, persistence, and degree completion in STEM-though the effect for cumulative GPA was small. In terms of degree completion, a student's chance of earning
a STEM-related bachelor's degree by Year 6 for those who met the STEM mathematics benchmark and had both expressed and measured interest in STEM was $50 \%$; it was $43 \%$ for those who met the benchmark but had neither expressed nor measured interest in STEM.

That being said, single-dimension measures of readiness have advantages as well. Single-dimension measures allow for monitoring over time of distinct dimensions of readiness. One of the primary uses of the ACT College Readiness Benchmarks is to provide targets for students in high school (and earlier grades) to work toward. The benchmark concept could be extended to multiple-dimension measures (e.g., based on a dichotomization of a readiness index that incorporates multiple measures such as high school courses taken and grades earned, measures of motivation and engagement, interest data, and ACT scores). While multiple-dimension measures are more predictive of college outcomes, single-dimension benchmarks are still useful because they are more informative of a student's specific areas of need.

Another limitation of the current study is the representativeness of the samples used to develop and validate the STEM readiness benchmarks. Even though the current study employed large, multiinstitutional samples of students and colleges, colleges in the southwest were overrepresented in the current study. There is no reason to expect that colleges in the southwest differ meaningfully from colleges located in other regions of the United States, but it is possible that the results could differ if more institutions from other regions were included in the analyses. To mitigate this issue, both institutional and student weighting was employed to ensure that the sample was representative of the larger population. Finally, the inability to completely differentiate between student transfers and dropouts and their effects on academic outcomes in Study 3 was a limitation. Future research should address such concerns.

Given the current national discourse focused on promoting STEM participation, the results suggest that caution should be taken against the blanket encouragement of all students to enter a STEM field, especially among those who will likely encounter academic hardships given their current level of academic preparation in mathematics and science. For example, among the 1.8 million ACT-tested high school graduates in 2014, the percentage of students meeting the ACT College Readiness Benchmark in mathematics and science were $43 \%$ and $37 \%$, respectively; the percentages drop to $16 \%$ and $23 \%$ for meeting the STEM readiness benchmarks in the same areas. The percentage meeting both is even lower: $13 \%$. These results suggest that simply promoting STEM participation is not a viable solution to the leaky STEM pipeline. Rather, preparing students academically and motivating them to pursue STEM fields as early as elementary and middle school is needed (Venkataraman, Riordan, \& Olson, 2010). By focusing on earlier grades, efforts can be directed at minimizing both the interest and achievement gaps often seen among females and minority students in STEM (e.g., OECD, 2014; Venkataraman et al., 2010). Such efforts would hopefully have the downstream effects of increasing the percentages of students graduating high school ready for STEM coursework to numbers higher than $16 \%$ in mathematics and $23 \%$ in science. Focusing on STEM readiness at the end of high school is too late to remedy the academic deficiencies and/or lack of interest (Doughterty, 2014; Mattern et al., 2014).

In sum, the goal of this research was to develop a metric that would be useful to students to gauge their preparedness for STEM-related coursework. Hopefully, for students who are not STEM ready but are interested in pursuing a STEM career, this information will compel them to take preemptive actions to further develop their knowledge and skills in these areas so that they are in a better position to achieve their educational and career aspirations and goals.

## Appendix

Table A1. Parameter Estimates from Hierarchical Logistic Regression Models for Course Success

| College course | ACT subject test | Mean/ variance | $B$ or higher |  | C or higher |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | Intercept (SE) | Slope (SE) | Intercept (SE) | Slope (SE) |
| Calculus | Mathematics | Mean | $\begin{aligned} & -4.247 \\ & (0.366) \end{aligned}$ | $\begin{gathered} 0.159 \\ (0.012) \end{gathered}$ | $\begin{aligned} & -2.693 \\ & (0.355) \end{aligned}$ | $\begin{gathered} 0.138 \\ (0.012) \end{gathered}$ |
|  |  | Variance | $\begin{gathered} 3.188 \\ (1.191) \end{gathered}$ | $\begin{gathered} 0.003 \\ (0.001) \end{gathered}$ | $\begin{gathered} 2.951 \\ (1.029) \end{gathered}$ | $\begin{gathered} 0.003 \\ (0.001) \end{gathered}$ |
| Combined Science | Science | Mean | $\begin{aligned} & -4.527 \\ & (0.210) \end{aligned}$ | $\begin{gathered} 0.180 \\ (0.008) \end{gathered}$ | $\begin{aligned} & -2.642 \\ & (0.202) \end{aligned}$ | $\begin{gathered} 0.152 \\ (0.008) \end{gathered}$ |
|  |  | Variance | $\begin{gathered} 3.857 \\ (0.662) \end{gathered}$ | $\begin{gathered} 0.005 \\ (0.001) \end{gathered}$ | $\begin{gathered} 3.514 \\ (0.637) \end{gathered}$ | $\begin{gathered} 0.005 \\ (0.001) \end{gathered}$ |

Note. Mean $=$ estimated mean value of parameter across institutions; variance $=$ estimated variance of parameter across institutions. Combined Science includes Biology, Chemistry, Physics, and Engineering courses. SE = standard error.

Table A2. Parameter Estimates from Hierarchical Logistic Regression Models for Students' Chances of Earning a 3.0 or Higher Cumulative GPA in STEM

| Subject area | Year | Mean/ variance | Intercept (SE) | STEM benchmark indicator (SE) |
| :---: | :---: | :---: | :---: | :---: |
| Mathematics | 1 | Mean | -0.461 | 1.367 |
|  |  |  | (0.056) | (0.058) |
|  |  | Variance | 0.124 | 0.062 |
|  |  |  | (0.030) | (0.027) |
|  | 2 | Mean | -0.098 | 1.262 |
|  |  |  | (0.054) | (0.058) |
|  |  | Variance | 0.106 | 0.031 |
|  |  |  | (0.028) | (0.018) |
|  | 3 | Mean | 0.111 | 1.160 |
|  |  |  | (0.063) | (0.059) |
|  |  | Variance | 0.145 | 0.021 |
|  |  |  | (0.038) | (0.015) |
|  | 4 | Mean | 0.265 | 1.103 |
|  |  |  | (0.068) | (0.065) |
|  |  | Variance | 0.164 | 0.036 |
|  |  |  | (0.043) | (0.022) |
| Science | 1 | Mean | -0.494 | 1.076 |
|  |  |  | (0.058) | (0.046) |
|  |  | Variance | 0.137 | 0.045 |
|  |  |  | (0.033) | (0.018) |
|  | 2 | Mean | -0.164 | 1.167 |
|  |  |  | (0.053) | (0.060) |
|  |  | Variance | 0.101 | 0.066 |
|  |  |  | (0.027) | (0.028) |
|  | 3 | Mean | 0.049 | 1.069 |
|  |  |  | (0.063) | (0.053) |
|  |  | Variance | 0.142 | 0.033 |
|  |  |  | (0.037) | (0.016) |
|  | 4 | Mean | 0.204 | 1.022 |
|  |  |  | (0.068) | (0.059) |
|  |  | Variance | 0.165 | 0.040 |
|  |  |  | (0.044) | (0.021) |

Note: Mean = estimated mean value of parameter across institutions; variance $=$ estimated variance of parameter across institutions. $\mathrm{SE}=$ standard error.

Table A3. Parameter Estimates from Hierarchical Multinomial Regression Models for STEM Persistence

| Subject area | Year | Mean/ variance | Not enrolled vs. persisted |  | Left STEM vs. persisted |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | Intercept (SE) | STEM benchmark indicator (SE) | Intercept (SE) | STEM benchmark indicator (SE) |
| Mathematics | 2 | Mean | -0.583 | -0.846 | -1.020 | -0.814 |
|  |  |  | (0.076) | (0.031) | (0.150) | (0.030) |
|  |  | Variance |  | - |  | - |
|  |  |  | (0.057) |  | (0.240) |  |
|  | 3 | Mean | -0.082 | -0.891 | -0.668 | -0.922 |
|  |  |  | (0.084) | (0.028) | (0.150) | (0.029) |
|  |  | Variance | 0.322 | - | 1.052 | - |
|  |  |  | (0.069) |  | (0.241) |  |
|  | 4 | Mean | 0.164 | -0.933 | -0.560 | -0.958 |
|  |  |  | (0.089) | (0.027) | (0.153) | (0.029) |
|  |  | Variance | 0.368 | - | 1.086 | - |
|  |  |  | (0.078) |  | (0.250) |  |
| Science | 2 | Mean | -0.569 | -0.658 | -1.011 | -0.618 |
|  |  |  | (0.080) | (0.027) | (0.152) | (0.027) |
|  |  |  | 0.287 | - | 1.081 | - |
|  |  | Variance | (0.062) |  | $(0.245)$ |  |
|  | 3 | Mean | -0.068 | -0.692 | -0.660 | -0.695 |
|  |  |  | (0.088) | (0.025) | (0.153) | (0.026) |
|  |  | Variance |  | - | 1.085 | - |
|  |  | Variance | (0.075) |  | (0.248) |  |
|  | 4 | Mean | 0.179 | -0.729 | -0.552 | -0.719 |
|  |  |  | (0.094) | (0.025) | (0.155) | (0.026) |
|  |  |  | 0.403 | - | 1.123 | - |
|  |  | Variance | (0.085) |  | $(0.258)$ |  |

Note: Slopes did not randomly vary across institutions; SE = standard error; mean = estimated mean value of parameter across institutions; variance $=$ estimated variance of parameter across institutions.

Table A4. Parameter Estimates from Hierarchical Discrete-Time Survival Models for STEM Degree Completion

|  | Mean/ | Mathematics |  | Science |
| :--- | :--- | :---: | :---: | :---: |
| Variable | variance | Estimate (SE) |  | Estimate (SE) |
| Term 6 | Mean | $-5.639(0.141)$ |  | $-5.644(0.143)$ |
|  | Variance | $0.507(0.166)$ |  | $0.526(0.170)$ |
| Term 7 | Mean | $-5.217(0.147)$ |  | $-5.225(0.148)$ |
|  | Variance | $0.678(0.198)$ |  | $0.687(0.198)$ |
| Term 8 | Mean | $-2.015(0.125)$ |  | $-2.038(0.129)$ |
|  | Variance | $0.714(0.160)$ |  | $0.755(0.169)$ |
| Term 9 | Mean | $-3.386(0.124)$ |  | $-3.412(0.129)$ |
|  | Variance | $0.583(0.147)$ |  | $0.632(0.158)$ |
| Term 10 | Mean | $-2.859(0.117)$ |  | $-2.891(0.121)$ |
|  | Variance | $0.540(0.132)$ |  | $0.586(0.142)$ |
| Term 11 | Mean | $-4.295(0.143)$ |  | $-4.321(0.145)$ |
|  | Variance | $0.496(0.162)$ |  | $0.518(0.167)$ |
| Term 12 | Mean | $-3.863(0.111)$ |  | $-3.894(0.114)$ |
|  | Variance | $0.279(0.097)$ |  | $0.306(0.104)$ |
| STEM Benchmark | Mean | $1.030(0.053)$ | $0.836(0.045)$ |  |
| Indicator | Variance | $0.071(0.023)$ | $0.048(0.016)$ |  |

Note: The term variables can be interpreted as Term $6=$ Spring/Summer term of Year 3, Term $7=$ Fall term of Year 4 through Term 12 = Spring/summer term of Year 6. Mean $=$ estimated mean value of parameter across institutions; variance $=$ estimated variance of parameter across institutions. $S E=$ standard error.

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[^0]:    ${ }^{1}$ Results are based on findings from the 1988 National Education Longitudinal Survey (Nels:88; National Center for Education Statistics, 1988). Analyses should be replicated with more recent cohorts to determine if these findings represent current trends.

[^1]:    ${ }^{2}$ The ACT College Readiness Benchmarks were updated in 2013 based on more current data. The new analyses revealed no change in the English and Mathematics Benchmarks of 18 and 22, respectively. The Reading Benchmark increased from 21 to 22, and the Science Benchmark decreased from 24 to 23 (Allen, 2013).
    ${ }^{3}$ In 2007, the College Board released benchmarks based on the previous version of the SAT, which did not include the writing section; the benchmark was derived based on the composite score of SAT Math + SAT Verbal (Kobrin, 2007).
    ${ }^{4}$ Benchmarks had previously been used for ACT Explore ${ }^{\oplus}$ (Grades 8 and 9) and ACT Plan ${ }^{\circledR}$ (grade 10).

[^2]:    ${ }^{7}$ Given the lack of consistency among the various STEM definitions being currently employed, ACT conducted a comprehensive review of the literature and provided a refined definition of STEM. One characteristic of ACT's definition is that it excludes social/behavioral sciences such as psychology and sociology (Green, 2007). To learn more about which majors and occupations are included in ACT's definition of STEM, see the original report (2014b).

[^3]:    Note. Percentages may not sum to $100 \%$ due to rounding
    a The number of students in this column is not the sum of the overall STEM column and the non-STEM students column. Students who were STEM majors for only one term in their first year were in the total group but not included in the subanalyses, given that they did not cleanly fall into either category.

[^4]:    ${ }^{8}$ Weighted percentages are reported. The sample was weighted to be similar to an ACT-tested, four-year college enrollee population with respect to institution admission selectivity (less versus more selective). The selectivity of admission policies was self-reported by the institutions using five levels that classified their level according to the typical ACT Composite score and high school ranks of their accepted freshmen. The population included a larger proportion of more selective institutions ( $39 \%$ selective versus $61 \%$ less selective) as compared to the sample ( $19 \%$ selective versus $81 \%$ less selective). See Tables 5 and 6 for more details about the population.

[^5]:    Note. Data are based on 27 public four-year, postsecondary institutions from three states ( 2005 through 2009 freshman cohorts). There were 100,954 total students, 22,113 first-year STEM majors, and 64,657 first-year non-STEM majors. The breakdown by STEM cluster was: 8,413 for science; 2,821 for computer science and mathematics; 3,780 for medical health; and 7,099 for engineering. Examples of courses included in the "Other" category include Elementary Functions, Introduction to Mathematics, and Linear Equation Inequalities. Percentages will sum to above 100\% due to the fact that some students took multiple mathematics courses in the same term.

[^6]:    ${ }^{9}$ For these three STEM clusters combined, $32 \%$ of STEM students took Calculus I as their first mathematics course and an additional 12\% took Calculus II.

[^7]:    ${ }^{10}$ These colleges and universities were determined using college enrollment records from the National Student Clearinghouse for all 2013 ACT-tested high school graduates who indicated that they planned to major in a STEM field ( $N=530,428$ students).
    ${ }^{11}$ Majors with the highest numbers of students interested in them by cluster were identified from ACT's Condition of STEM report (2014).
    ${ }^{12}$ This criterion is also used in ACT Course Placement Research services to avoid having intervening coursework influence test scorecourse outcome relationships.

[^8]:    ${ }^{13}$ Student weighting was employed to ensure that the sample was representative of a larger population of ACT-tested high school graduates in terms of race/ethnicity, ACT Composite score, and HSGPA. This is the population to which the ACT College Readiness Benchmarks are reported on and thus the envisioned group to whom the STEM-specific benchmarks would be conveyed to (if not earlier).

[^9]:    ${ }^{14}$ Institutional weighting consisted of applying weights to the institution specific cut scores to make each sample similar to an ACTtested four-year-college-enrollee population with respect to both institutional selectivity and size. Similar results were obtained when weighting only took into account institutional selectivity and did not give more weight to larger institutions.

[^10]:    ${ }^{15}$ All students who took Calculus I as their first mathematics course were included in the analyses. Students taking a Survey of Calculus course were not included. The sample was not restricted to STEM majors. Given the concern that Calculus courses taken by STEM majors may be more difficult than Calculus courses taken by non-STEM majors, follow-up analyses were conducted to determine whether differences would arise if the sample had been restricted to STEM majors. Identical results were found, supporting the generalizability of the findings.
    ${ }^{16}$ Additional data cleaning of the science course data was conducted. Specifically, only science courses that fulfilled course requirements for science majors were analyzed; science courses that were offered to non-science majors were excluded. This included the removal of 2,427 student records for Chemistry and 9,784 student records for Biology.

[^11]:    ${ }^{17}$ First-year STEM majors included 49,917 (94\%) who declared a STEM major during their first fall term and 3,192 (6\%) who were undeclared during their first fall term but declared a STEM major during their first spring term. Longitudinal data was available on STEM majors entering college in 2005 through 2009. For earlier cohorts, up to eight years of outcome data were available. For the most recent cohorts, at least four years of longitudinal data were available. For two state systems, students were tracked across instate institutions.

[^12]:    ${ }^{18}$ Institutions provided six-digit CIP codes over time for each term enrolled.
    ${ }^{19}$ For persistence in STEM, a random intercept and slope model did not converge for either STEM readiness benchmark for all outcomes, most likely because the variance estimate of the STEM readiness indicator was close to 0 . For the instances where the results did converge, the random intercept model and the random intercept and slope model provided nearly identical results. Results for the random intercept model are reported.

