Predictive Power of Sixth-Grade Achievement on Secondary Chemistry Academic Outcomes

Nathan Lee Charnock
Hillsborough County Public Schools

Steven Alan Hecht
Nova Southeastern University

Abstract

The purpose of this study was to identify student level characteristics that predicted both enrollment and achievement in 10th-grade chemistry courses. We obtained a large representative sample from an academic cohort drawn from a mid-sized metropolitan school district in Florida. Predictors were derived from school district archived data for sixth-grade students whom latter completed a science course in their sophomore year of high school. The predictors included letter grades, standardized test scores on the Florida Comprehensive Assessment Test (FCAT), attendance rate, number of suspensions, and demographic data. Logistic regression demonstrated specificity for particular student attributes that contribute to the odds of enrollment into and, independently, the probability of successful chemistry courses achievement. The results demonstrated that female students were more likely to enroll in and pass a chemistry course than their male peers. Prior science achievement was the strongest predictor of high school chemistry course outcomes.

Keywords: high school chemistry, logistic regression, secondary achievement, middle grades achievement

Introduction

The purpose of this study was to examine what early variables best predict high school chemistry outcomes. The construction of this predictive model grew out of an unprecedented demand for accountability, efficiency, and effectiveness among schools, students, and staff. To meet this demand, policy makers and stakeholders increasingly have become focused on approaches that increase student achievement as measured by standardized high-stakes tests, resulting in retroactive data analysis and policy designing (Moses & Nanna, 2007). Predictive modeling is a direct and proactive method by which an organization may anticipate student course- enrollment behavior and the odds of successful course outcomes (Goenner & Pauls, 2006; Smith, Lange, & Huston, 2012). Similarly, Johnson et al. (2012) demonstrated that logistic regression models could be constructed from archival student data and reliably predict student performance on the State of Texas Assessment of Academic Readiness (STAAR) chemistry exam for a small concurrent convenience sample of 32 10th- and 68 11th-graders (N = 100).

Johnson et al.'s (2012) study used three years of previous standardized science achievement tests scores as predictors in their logistic regression model. The logistic regression was model was reported to accurately predicted nearly 93% of student outcomes where 53 out of 56 students were correctly predicted to have passed the STAAR exam and 41 out of 44 students were predicted to have failed the STAAR exam (Johnson et al., 2012).

Though admission requirements for Universities vary greatly, Florida Board of Governors Regulation 6.002 (2016) requires 3.0 credits in the natural sciences. Thus, high school chemistry course completion is typically considered an essential for college- bound students (Gardner, et al., 1983; Sadler, & Tai, 2000; Walford, 1983). Within the secondary setting, successful completion of the course generally serves as a prerequisite to- and to a lesser extent, a gatekeeper for- subsequent enrollment into more advanced science courses.

The goal of this study was to identify student characteristics in sixth-grade that enhanced or hindered 10th-grade chemistry outcomes, preceding high school matriculation. The author's intent is to provide an empirical means by which school districts may choose to employ to inform on decisions that lead to an increase in the number of students whom are authentically prepared to enroll in—and succeed at—a high school chemistry. An effective model for predicting course enrollment and successful achievement would be helpful in this objective. This model would be a tool that could aid administrators in efficiently employing pedagogical or instructional interventions. Once reliable predictors of success are identified, students whom are at risk for a diminished likelihood of enrollment or achievement could be strategically targeted for early intervention (Maki, 2004). This early identification could enhance student-specific need-based preparation, which may lead to increased levels of student achievement in the short term (Cooper & Pearson, 2012). The short- term effects could give rise to downstream learning gains that might lead to increased enrollment into this gatekeeper course. Early intervention could also have a more global impact on student preparedness that possibly results in an improvement in the overall magnitude of course achievement (Cooper & Pearson, 2012; Maki, 2004). To explore the plausibility and reliability of a model to make such early predictions three theoretical views were investigated.

Theoretical Framework

This study examined the factors that independently predicted the odds of enrollment and passing a 10th-grade chemistry course. The results of this study are useful to identify sixth-grade students whom are not likely to either enroll or succeed in a secondary chemistry course. As such, this study is exploratory in nature. Regarding the theoretical framework of this study, there are three alternative views concerning the nature of the relations between sixth-grade student attributes and 10th-grade chemistry outcomes. The first is that level of prior achievement in mathematics and/or science in sixth-grade is key to future success. In this way, success in chemistry-related coursework acts as a bottleneck for pathways into chemistry and serves as an impediment to future achievement (see Figure 1). An alternative view is that generalized achievement is key; such that prior mathematics, science, and more general reading- intensive courses (e.g., English and/or history) all uniquely predict 10th-grade chemistry outcomes (see Figure 2). Finally, a third view suggested by the literature is that attendance, demographics, and/or receipt of exceptional learning service uniquely contribute to 10th-grade chemistry performance, after controlling for each other and prior academic achievement (see Figure 3). It is noted that for parsimony the third alternative view does not make any claims concerning which of the academic achievement areas uniquely predict 10th-grade chemistry outcomes.

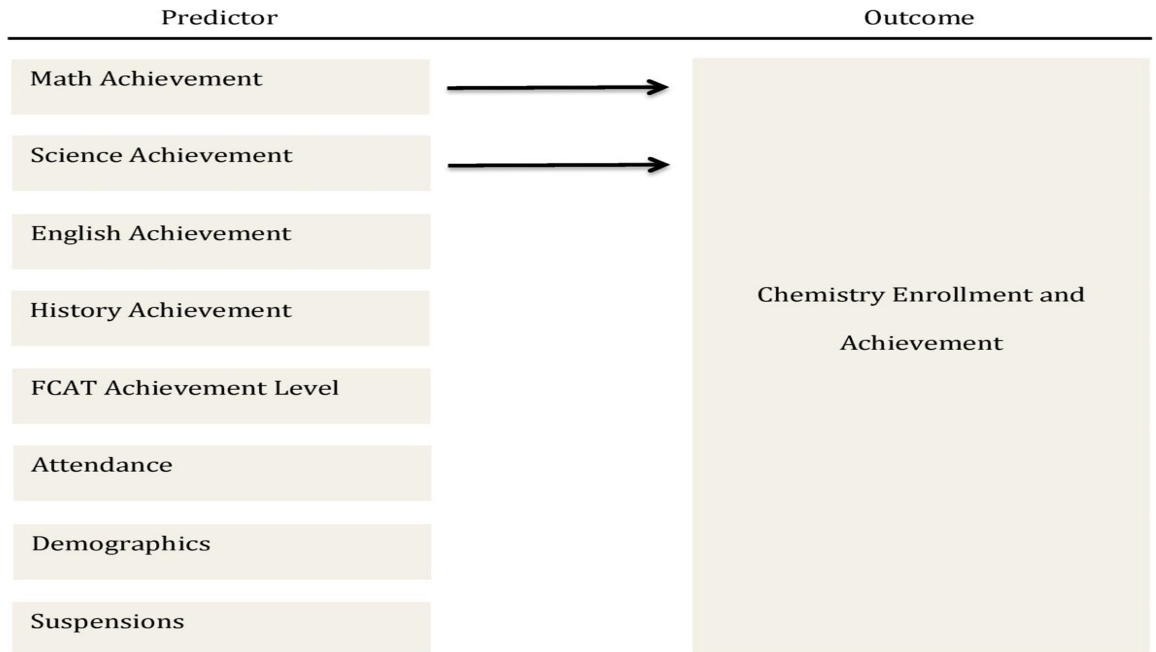

Figure 1. First view: Only prior mathematics and science achievement are uniquely predictive of future chemistry outcomes (as depicted by the arrows).

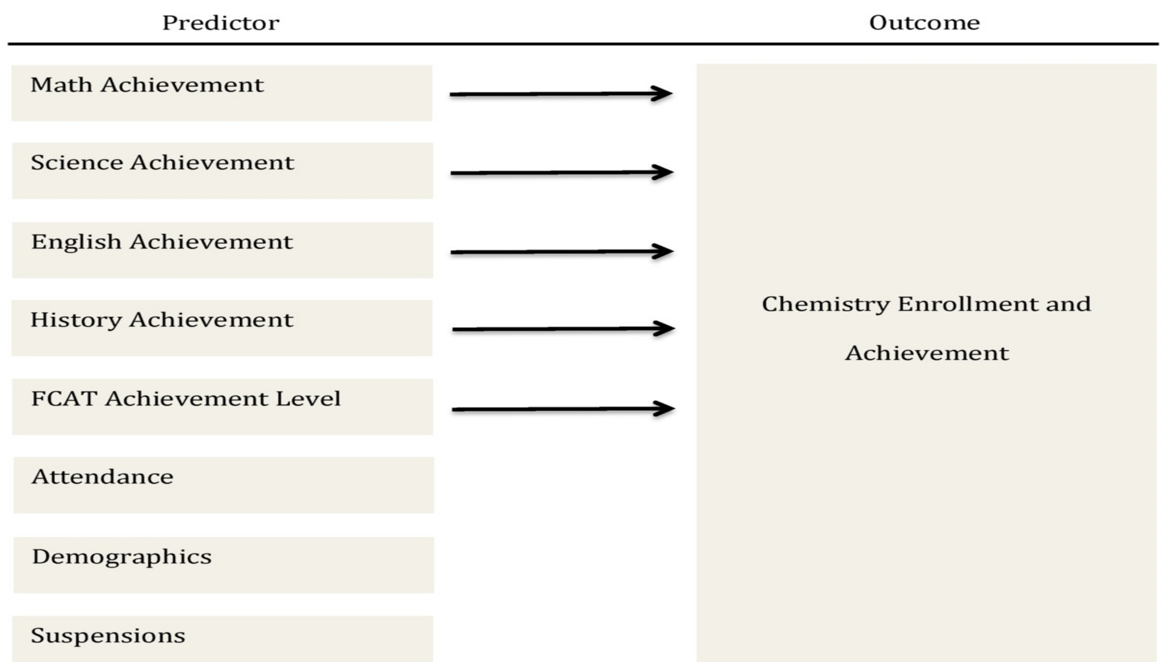

Figure 2. Second view: Prior mathematics and science and more general reading intensive courses such as English and/or history all uniquely predict 10th-grade chemistry course achievement (as depicted by the arrows).

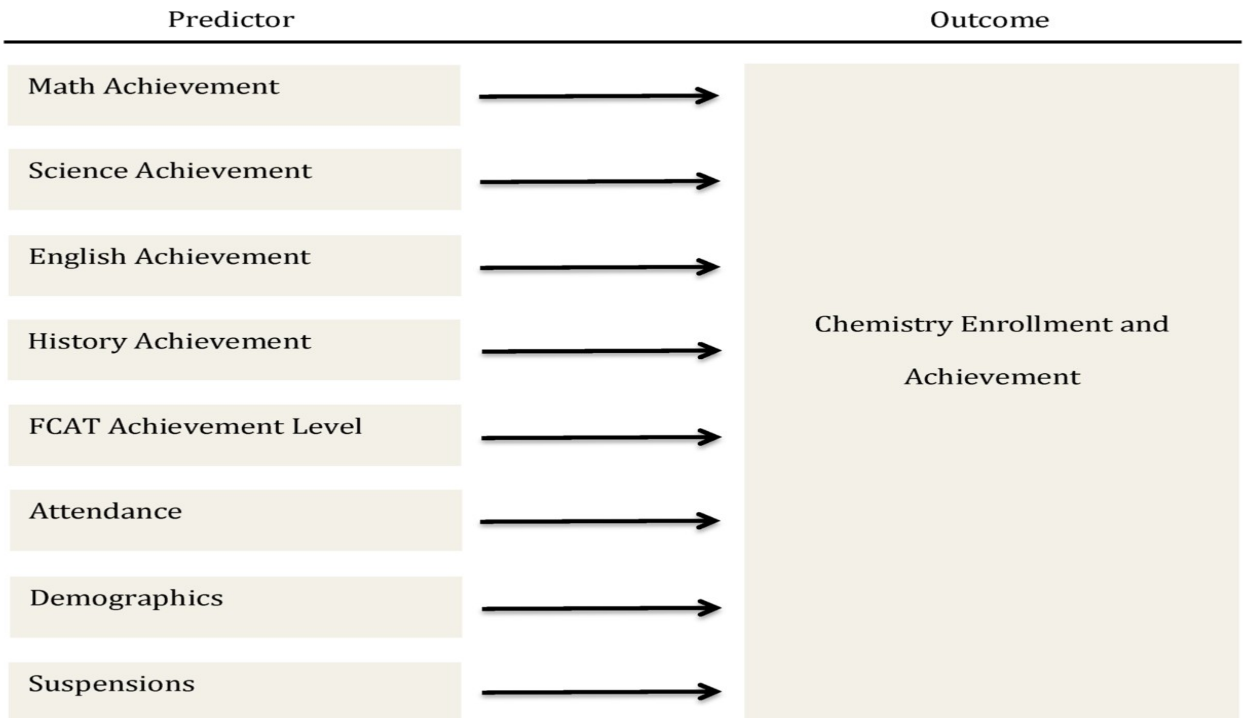

Figure 3. Third view: Prior academic achievement, student demographics, and behavior are uniquely predictive of future chemistry outcomes (as depicted by the arrows).

To evaluate each of the theoretical models, logistic regression was employed to determine the odds of chemistry course enrollment and the likelihood of a positive academic outcome from predictors derived from students' archived sixth-grade data. The predictors were prior academic course achievement; Florida Comprehensive Assessment Test (FCAT) achievement levels; data for rates of absenteeism and suspension; and the following student demographic characteristics of: gender, socioeconomic status (SES), exceptional student education (ESE) and/or English language learner (ELL) services, and race. Prior academic course achievement was operationalized as the cumulative, numerically transformed letter grades of each quarter's coursework completed in mathematics, English, history, and science. This cumulative grade point average (GPA) for each academic discipline was evaluated while considering and controlling for FCAT achievement levels. In addition, the relative importance of demographics, SES, and ESE and/or ELL services was also considered. Finally, all cases in this study were assessed for the relative effects of rates of absenteeism and classroom behavior as indicated by number of days suspended (excluding all school bus suspensions) for chemistry course outcomes. Each logistic regression model was done to examine malleable factors that might contribute to both the odds of both chemistry course enrollment and achievement and thus should be targeted in future interventions.

Background

Concern for accountability for student achievement is a reasonably persistent issue of social importance. Accountability, in terms of student progress, is in concert with the general perception that any improvement in course achievement at the student level implies both instructional and institutional effectiveness (Borden & Young, 2008; Kim, Zabel, Stiefel, & Schwartz, 2006; Maki, 2004). This general perception is supported by research indicating that prior course achievement is strongly predictive of future achievement in subsequent math and reading intensive courses in secondary education (Craney & Armstrong, 1985; Duncan et al., 2007; Hemmings, Grootenboer, & Kay, 2011; House, Hurst, & Keely, 1996; McKenzie & Schweitzer, 2001; Watts, Duncan, Siegler, & Davis-Kean, 2014; Zeegers, 2004).

Various theoretical frameworks are used as a means to measure an institution's effectiveness as a function of student achievement. Through these frameworks, many predictive models specifically evaluate academic achievement at the student level (Maki, 2004). Although predictive models generally fall within the same theoretical framework, naturally, each study operationalizes variables differently to properly address a range of research questions specific to each investigation pertaining to student achievement (Ayan & Garcia, 2008; Goenner & Snaith, 2004; Nonis & Wright, 2003). This study employed logistic regression methods because of the efficiency in which a group of independent variables are evaluated for effects on a binary outcome. Systematically the independent variable's unique contribution can be quantified by iteratively identifying the strongest combination of variables with the greatest probability of detecting the observed outcome. The strength of the logistic approach lies in the fact that there is one linear decision boundary for each dichotomous outcome. Because the underlying dependent variables modeled are binary and have the values Yes (student enrolled) or No (student did not enroll); likewise, Pass (student passed chemistry) or Fail (student failed chemistry), ordinary least squares regression cannot be used as assumptions of normality of the responses and homoscedasticity of the residuals will be violated (Cohen et al., 2003). Beyond theoretical nuances, this approach may be attractive to districts acting as practitioners, for this model is easily built and evaluated from local digital data archives to answer similar research question related to future enrollment and/or achievement.

Research Questions

1. Does academic achievement—as measured by course-letter grades earned for sixth-grade mathematics, English literacy, history, science, and FCAT (achievement level) — accurately predict the proportion of students who enroll in chemistry or an equivalent science course in the 10th-grade?
2. Do student characteristics (gender, race, SES, ESE and/or ELL status) uniquely predict chemistry enrollment after controlling for the effects of sixth-grade academic achievement and FCAT subtest level?
3. Does absenteeism and/or number of suspensions in the sixth-grade uniquely predict 10th-grade chemistry enrollment after controlling for course academic course achievement, FCAT mathematics and reading achievement levels, and student characteristics?
4. Do sixth-grade course-letter grades for mathematics, English literacy, history, science, and FCAT achievement accurately predict the proportion of students who pass chemistry in the 10th-grade?
5. Do student characteristics (gender, race, SES, ESE/ELL) uniquely predict passing chemistry in the 10th-grade while controlling for the academic achievement and standardized test scores?
6. Do student absences and/or number of suspensions in sixth-grade uniquely predict passing chemistry in the 10th-grade while controlling for the effects of prior grades, standardized test scores, and student characteristics?

To explore the research questions, we employed an archived sixth-grade dataset consisting of a cohort of public school students from a mid-sized metropolitan area in Florida. Prior research has addressed disparities in the postsecondary setting. The disparities addressed are generally limited to post-secondary chemistry course achievement and persistence in science, technology, engineering, and mathematics (STEM) majors (Craney & Armstrong, 1985; Easter, 2010). The literature has consistently identified chemistry as a gatekeeper for subsequent science coursework (Chambers, 2005; Easter, 2010). We now comprehensively review key findings from the existing literature base focusing on individual differences in postsecondary chemistry outcomes. We also relate this prior work to our current focus on secondary school level chemistry outcomes.

Though discussion in the literature has persisted for over 100 years, postsecondary education enrollment in the STEM fields has received an increase of attention since the 1970s, particularly as it is critical for enhancing the national economy (Gardner, et al., 1983; Gasiewski, Eagan, Garcia, Hurtado, & Chang, 2011). Growing concern for America's ability to maintain its competitive position in the global marketplace has placed new scrutiny on the education system at all levels. This demand requires the modern education system to produce more graduates with expertise in STEM fields. Yet Gasiewski et al. (2011) reported that introductory STEM courses remain gatekeepers into the STEM fields. Despite a national sense of urgency, the percentage of U.S. undergraduates pursuing and earning STEM degrees has changed little over the years (Eagan, Hurtado, Figueroa, & Hughes, n.d.; Gardner, et al., 1983). Between 2003 and 2009, persistence of enrollment in STEM fields accounted for 63.8% of all bachelor's-degree-seeking students; by 2009, 30.9% of students enrolled either withdrew or failed at least one core course in the STEM pipeline, and 48.3% either left college without a degree or switched to a different major (Chen & Ho, 2012). Chen and Soldner (2013) reported that the physical sciences in particular have a 48% rate of attrition resulting in a change of major or complete withdraw from college (n = 7,800). Non-STEM majors were reported to experience similar attrition rates in the social/behavioral sciences as a function of a change in major (Chen & Soldner, 2013). Whereas, the number of non-STEM students withdrawing from college without earning a degree was 234 fewer than those enrolled in STEM majors (Chen & Soldner, 2013).

To better understand and explain these trends researchers have consistently documented correlations between secondary and postsecondary outcomes. For example, comparing secondary and postsecondary outcomes, Sawyer (2010) calculated correlations of high school rank, grades, and SAT scores with 1st-year college GPA in a study encompassing the 1976–1985 academic years. Historically, over this time span, multiple correlations for high school rank and grades ranged from r = .48 to .52; thus, 23–27% of 1st-year college GPA variance could be explained by student rank within their high school and grades on college GPA (Sawyer, 2010). Further, Noble and Sawyer (1987) reported that as much as 39% of the variance at the postsecondary level for chemistry course achievement was attributed to performance in high school chemistry coursework. Another study by Geiser and Santelices (2007) found that high school mathematics, social sciences, and other academic classes accounted for 26.3%, 31.2%, and 29.4% of the variance, respectively, for final college GPA in three large samples of students. These predictive relations remain after controlling for SES, with high school GPA accounting for 24.0% of the variance explained in 1st-year college achievement for students continuously enrolled in the same school district from Grades 1–8 (Wilson, 1983).

Considering standardized college entrance tests, Noble and Sawyer (1987) reported that ACT composite scores explained 23.8% of the variance in achievement in terms of overall GPA in 1st-year college students (n = 919) and 51% of the variance in college chemistry achievement in terms of course GPA for a sample of 191,626 college students, where as much as 39% of the variance was explained by the students' high school chemistry grade. Noble and Sawyer's (1987) finding suggest that the first theoretical model proposed by this study would likely be supported. Additionally, Noble and Sawyer (1987) reported that the SAT Mathematics and Verbal subtests accounted for 45% and 23% of the variance, respectively, for achievement among 1st-year students (n = 1,032). Hayali (2013) independently reported that the SAT composite score explained 40.2% of the variance (n = 4,707). Findings from Noble and Sawyer, are independently supported by Hayali regarding the significance of relevant standardized testing on the likelihood of future academic outcome. This further suggests that the first theoretical model considering FCAT achievement levels proposed by this study would likely enhance the magnitude of effect size observed for logistic regression outcomes when considered with course specific academic predictors.

Variables that predict college enrollment into rigorous science majors is of critical concern. The physical sciences make up 32.6% of the total STEM enrollment rate, of which only 54% of students persisted in a major for the physical sciences, indicating an attrition rate of 46% which means only 17% are graduating with a physical science degree (National Center for Education Statistics, 2012). The data focused on the enrollment and attrition of first-time 1st-year college students indicated that the majority of attrition occurs within the first 2 years of STEM coursework (Gasiewski et al., 2011; Laird, Alt, & Wu, 2009). For those students who have successfully completed a STEM degree program, students who had a high school

GPA of 3.0 or higher were 10.3 times more likely to successfully complete a STEM program than those entering with a GPA of 2.0 or lower (Johnson, Johnson, & Johnson, 2012; Laird et al., 2009).

The literature that explored postsecondary chemistry outcomes indicated that prior mathematics course success and standardized test performance are both uniquely important for predicting student variability in chemistry outcomes (Nordstrom, 1990; Pugh & Lowther, 2004; Zuidema & Eames, 2014). Among the most prevalent predictors reported for general college chemistry achievement are the scores earned on the either the Scholastic Achievement Test (SAT) or American College Testing (ACT) program, which are often coupled with high school grades in chemistry or mathematics, overall high school GPA, and institution-specific chemistry placement exams. A significant amount of first-year student-level variance at the postsecondary level can be accounted for by prior achievement (Nordstrom, 1990; Zuidema & Eames, 2014). The literature has also described a significant link between prior achievement in elementary, middle, and high school courses, which has also explained a large amount of student-level variance for achievement in the postsecondary setting (Nordstrom, 1990; Pugh & Lowther, 2004; Zuidema & Eames, 2014).

An examination of sixth-grade predictors on the high school chemistry outcome is analogous to predictions made about the likelihood of student achievement in the 1st-year of college based on high school predictors. It is likely that those findings could very well generalize to younger students, such as predicting high school outcomes from predictors based on data gathered from elementary or middle school (Scafidi & Bui, 2010; Seery, 2009). It is therefore reasonable to expect a relationship between prior achievement in the sixth-grade and secondary chemistry outcomes and is justification for the current study.

The Current Study

Although high school achievement, in terms of cumulative GPA or final chemistry course grade is considered a predictive indicator for college achievement in general chemistry. Few studies have explored which variables significantly predict chemistry performance in high school. Rather, most reported work has focused on high school outcomes for mathematical skills, English proficiency, or factors that contribute to accurately predicting the likelihood of high school graduation (Balfanz & Byrnes, 2009; Balfanz, Herzog, & MacIver, 2007; Guthrie & Davis, 2010; Nizoloman, 2013; Useem, 2010; Wang & Goldschmidt, 2010).

Likewise, the research literature also fails to address any combination of predictors that account for characteristics that model longitudinal outcomes in terms of either enrollment or achievement in secondary science and in particular for the chemistry course. The research only reflects a scant number of articles that investigated singular inputs for their effects on chemistry outcomes. There are no large-scale studies employing data from an entire cohort of students served by a large urban school district with respect to predicting chemistry outcomes.

Specifically, a Boolean search on the Education Resources Information Center (ERIC) for predicting high school chemistry achievement yielded 16 peer-reviewed articles spanning 49 years of research; of the articles, only one was relevant to carrying out predictive modeling for secondary chemistry course achievement. Of particular relevance was a study performed by W. L. Johnson et al. (2012), where a convenience sample of 100 students was analyzed to determine the probability of their successfully completing the Texas chemistry end-of-course test, known as the State of Texas Assessments of Academic Readiness (STAAR). W. L. Johnson et al.'s logistic model was limited to just one the prior year's performance on a sole predictor, a standardized science assessment (independent variable) and the STAAR pilot-test results (dependent variable) for the same students.

A Boolean search of the ERIC database for high school chemistry achievement returned 590 peer-reviewed articles, representing 49 years of research. After controlling for W. L. Johnson et al.'s (2012) study, there were no relevant reports for predicting high school chemistry course achievement. A final

Boolean search in the ERIC database for predicting secondary chemistry achievement returned five results, and, again, W. L. Johnson et al.'s article, there were no remaining relevant reports. Likewise, high school chemistry course achievement has not been a focus of predictive modeling and no reported model has attempted to predict the probability of enrollment into high school chemistry courses (Grier, 2012; Johnson, W. L., et al., 2012; O'Connor, Miranda, & Beasley, 1999; Walberg, 1992; Zins et al., 2004).

In addition to searching the conventional literature repositories, an additional search explored the search terms described above via Google Scholar. This literature search yielded the same lack of empirical studies with specificity for high school chemistry enrollment or achievement outcomes. Thus, the current study provides the most comprehensive examination of predictors of high school chemistry outcomes by examining a more comprehensive set of predictors, including variables that are routinely gathered by school districts and that are likely malleable and therefore relevant for future interventions. The exceptionality of this study is its' intentional novelty of a ubiquitous approach which may be easily adapted to model trends for adjacent courses.

Significant predictors and accurate predictive models of student enrollment and success have been long sought after in the field of education. Research has primarily focused on domains such as mathematics, English literacy, behavior, and attendance for effects on enrollment and achievement to shape policy and drive curriculum reform (Bodovski, Nahum-Shani, & Walsh, 2013; Gu, Solomon, Zhang, & Xiang, 2011; Gullo, 2013; Hauptli & Cohen-Vogel, 2013; Obrentz, 2012; Vigdor, 2012). Such findings represent a growing body of evidence indicating how students learn and conceptualize (or incorrectly conceptualize) topics in the physical sciences (Christian & Yezierski, 2012; Cokelez, 2012; Luxford & Bretz, 2014; Newman, 2013; Ramful & Narod, 2014). This study contributed to this growing body of literature through an investigation of predictors of student enrollment and achievement in secondary chemistry courses by means of logistic regression.

Before designing and implementing any pedagogical or instructional interventions to improve student achievement, it is important to develop an effective model to predict the odds of student enrollment and successful course achievement. Early identification of at-risk students will enable researchers and practitioners to develop effective interventions that target and address student learning deficits that could improve the odds of chemistry outcomes (Maki, 2004).

Currently, there are no longitudinal predictive models based on a large and representative school district sample allowing for reliable and accurate prediction of either the prevalence of student enrollment or the likelihood of passing a secondary chemistry course. Institutionally, identifying and targeting at-risk students before entry into the secondary system would allow for a more efficient allocation of resources. Predictive modeling enables administrators to make informed decisions on strategically managing human capital. Through strategic resource management, specific pedagogical needs at the student, classroom, and school levels may be more efficiently and economically addressed. This may enhance the frequency of future course enrollment and increase the magnitude of student success (Wagner, Sasser, & DiBiase, 2002).

To achieve this goal, two separate predictive models were developed and tested, in parallel, to evaluate the significance of selected inputs for predictive power and reliability. The relative level of significant contribution made by each input was assessed in terms of effect size, as measured by Cohen's *d* or odds ratio where appropriate (Sánchez-Meca, Marín-Martínez, & Chacón- Moscoso, 2003).

Method

Participants

The sample consisted of students who completed a chemistry course or in a science course in lieu of chemistry for the 2013 academic year. The sample for this study was drawn from an academic cohort for a single metropolitan school district in Florida, ranking in the top 10 largest districts in the nation. Across the district, total enrollment was 195,783 students for the 2013 academic year. Of the students in the research cohort, 51% were female, and the racial composition (self-identified) was as follows: < 1% American Native, 3% Asian, 21% Black, 32% Hispanic, and 38% White. For the students constituting the research cohort, nearly 57% were eligible for either free or reduced-price lunch, 14% were identified as eligible for or a recipient of ESE services, and 11% were identified as in an English language learner (ELL) status or recipient of services (Florida Department of Education, 2013).

Data Collection

The raw research data were collected in collaboration with the participating school district. In obtaining the de-identified archived student data, students were initially considered if identified for completion of a high school chemistry course or a science course in lieu of chemistry during the 2013 academic year. Once selected for preliminary consideration then, academic, number of suspensions, demographic, and ESE/ELL data points were extracted for the entire cohort for both their 10th- and all sixth-grade academic years. Specifically, the data for each case included the following:

- each student's quarterly letter grade awarded for each core course of study completed in mathematics, English literacy, history, and science;
- each student's FCAT subtest (mathematics and reading) performance band score;
- each student's sixth-grade attendance;
- the total number of each type of suspension, including external, internal, alternatives to external, and bus suspensions;
- student's gender;
- student's race;
- free or reduced-price lunch status; and
- receipt of special learning services for either ESE and/or ELL.

Prior to the release of the raw research data, each case was assigned a case number by the county Assessment Department; thus, cases were not identifiable by the principal investigator or authorized viewers. The first author kept the research data on a secure password-protected file until the end of the research project. At the end of the project, the author's data was destroyed in accordance with the school district's policy. The participating school district agreed to maintain a duplicate copy of the raw data for a minimum period of three years after the completion of this study.

Inclusion and Exclusion Criteria

The research cohort initially included any student who had completed a course in high school chemistry, or a course in lieu thereof, during the 2013 academic year. To qualify for inclusion, each student had to be continuously enrolled within the same district in Grades 6–10. Any student who had discontinued enrollment, withdrew from the chemistry course during the 2013 academic year, or had failed the chemistry course was excluded from the research cohort (as this was beyond the scope of the project). Additionally, case exclusion from the research cohort occurred for any student who had enrolled in or completed the chemistry course online (also beyond the scope of this project).

Preliminary Data Processing

Data Cleaning

De-identified student data consisted of 29 separate data files, each containing grade-level specific data for demographics, special learning services, absenteeism, suspension by type, academic achievement by quarter, and FCAT achievement data for Grades 6 and 10. The files were merged, and the data were filtered for missing demographic and missing science achievement data. Cases without demographic or 10th-grade outcomes were deleted list-wise.

To constitute the research database, first the academic records were combined by subject, this was done in order to represent a full year's academic progress in a given course of study. In consolidation, we considered all course levels (regular, honors, or advance placement) equivalent. However, remedial courses not recognized by the Florida Department of Education for core academic credit were not considered equivalent and were eliminated from further evaluation. Next, quarter letter grades were transformed into an ordered numeric value (A = 4.0, B = 3.0, C = 2.0, D = 1.0, F = 0), and each academic discipline's GPA was calculated. For cases with multiple enrollments for courses of the same discipline, the average of those courses' GPA was calculated and was used singularly for the applicable discipline. After each discipline's GPA was calculated, the FCAT achievement level and demographics data were added to the research database via the SPSS "merge file" command. Afterwards, consistent with the existing literature (Grosset & Hawk, 1986), students who had received free or reduced-price lunch were identified as economically vulnerable; in these cases, the SES value was set to one (affirming the dichotomous outcome as a positive integer).

For students who were not identified by the aforementioned SES criteria, the SES value was set to zero (Grosset & Hawk, 1986). Later, students eligible to received ESE and/or ELL services were assigned a value of one to indicate special learning service; for students who did not receive either ESE or ELL services, the value was set to zero. It must be noted that the ESE services can be classified categorically by type and separately by severity; however, this was beyond the scope of this study. Therefore, a student who received any ESE and/or ELL service, regardless of level of severity, was included in either the ESE and/or ELL predictor as appropriate and this excluded the gifted ESE designation. Discerning between a general education student and an ESE student classified as gifted was beyond the scope of this study.

The total number of days a student was present was calculated from the total number of days enrolled less the total number of days absent. The total number of days absent was reported by the district but collinearity was a concern. To control for collinearity issues that arise when considering suspension rates as a predictor the total number of days a student was externally suspended was subtracted from the total number of days absent. This was necessary because each day a student was externally suspended also counted as an unexcused absence according to the school district's discipline policy. The suspension rate variable also included the total number of days a student was internally or participated in the district's alternative-to-external suspension program (EPIC). A note on the district's EPIC program; the EPIC program allows students to service day(s) suspended in an alternative educational environment removed from the student's regular school site. The number of days suspended from a school bus, however, was excluded because the student might have been suspended from the school bus without being concurrently suspended from school.

Missing Data

Cases missing attendance, behavioral, or demographic data were excluded from the study. Cases with missing data for the following academic predictors: mathematics, English, history, science, or FCAT achievement level were replaced with expectation-maximization (EM) generated values, excluding the science outcomes for 10th-grade; if the case had a missing data point for this field, the case was deleted from the list. The EM method was selected because it overcomes many of the limitations of other techniques for addressing missing data, such as mean replacement and case-wise deletion. Either of which can result in an underestimation in parameter estimation or bias the results (Dong & Peng, 2013; Zhou & Lim, 2014). When using archived student records it is a reasonable expectation for some data to be missing by semester for some academic course outcomes, by student, for any given discipline in a non-systematic way. For example, such as when students dis-enrolled from a course of study, enrolled in a course of study out of sequence, or earned partial credit for a course of study via nontraditional means (online virtual school or credit recovery). So, to this end, EM replacement only occurred for missing achievement data, excluding replacement for the dependent variables. Also, for parsimony, none of the demographic, attendance, or behavioral predictors were replaced; if the case were missing data in one of these areas, the entire case was deleted from the database. To replace the missing data for the appropriate variables of interest, a 1,000-iteration EM algorithmic model replaced the missing achievement data (see Table 1). Then, a post hoc t test analysis revealed and demonstrated no significant difference between the replaced data and the original data for each of the variables with missing values (see Table 2).

Table 1. *Frequency of Available and Missing Sixth-Grade Predictor Variable Data Considered Separately With Raw and Expectation Maximization (EM) Replaced Mean and Standard Deviation, per Variable.*

	n available		*n* missing		Raw missing		EM-replaced	
Variable	Grade 6	Grade 10	Grade 6	Grade 10	Grade 6 M (SD)	Grade 10 M (SD)	Grade 6 M (SD)	Grade 10 M (SD)
Math	10,139	—	3,616	—	2.9 (1.0)	2.2 (1.1)	2.9 (1.0)	2.1 (1.1)
English	10,142	—	3,613	—	3.1 (1.0)	2.6 (1.1)	3.1 (1.0)	2.6 (1.1)
Science	10,152	12,074	3,603	1,681	3.0 (1.0)	2.4 (1.0)	3.0 (1.0)	2.4 (1.1)
History	10,136	—	3,619	—	3.1 (1.0)	2.6 (1.0)	3.1 (1.0)	2.6 (1.0)
Chemistry	—	5,953	—	23	—	—	—	—
FCAT reading	10,339	—	3,416	—	3.0 (1.2)	2.7 (1.3)	3.0 (1.2)	2.7 (1.2)
FCAT math	10,331	—	3,424	—	2.8 (1.3)	2.2 (1.3)	2.8 (1.3)	2.2 (1.3)

Note. N = 12,102. Outcome excludes EM-replaced data in all analyses. FCAT = Florida Comprehensive Assessment Test.

Table 2. Frequency of Available and Missing Data per Sixth-Grade Predictor Variable, Without Consideration of Missing Data for Other Variables or Other Grades Pairwise.

Variable	t (df)	p	Test value
Math	-.02 (1)	.985	2.61
English	.02 (1)	.987	2.60
Science[1]	.08 (1)	.942	2.68
History	.02 (1)	.984	2.83
FCAT reading	-.20 (1)	.853	2.83
FCAT math	-.01 (1)	.999	2.20

Note. n = 5,966. FCAT = Florida Comprehensive Assessment Test. [1]Indicates the exclusion of the outcome variables.

Variables

Academic Achievement

For this study, academic achievement was defined as the average of each quarter's letter grades earned in sixth-grade for English, history, and science. The academic disciplines' GPAs were calculated by taking the sum of each quarter's letter grade for each individual course of study. This was accomplished by re-coding each letter grade to an ordinal numeric value, to yield individual performance addends. Then, course GPAs were calculated by taking the summation of the addends divided by the number of quarters the student was enrolled in the course of study. The quotient of which was used as the course GPA input for modeling.

Standardized Testing

Standardized test predictors were derived from the performance bands (achievement levels) of the sixth-grade FCAT mathematics and reading subtests. These bands range from one, which indicates the student demonstrated an inadequate level of success with mastery of content as defined by Next Generation Sunshine State Standards (NGSSS) to five, by which the student demonstrated master of the most challenging content of the NGSSS (FLDOE, 2014). Buck, Torgesen, and Schatschneider (2001) previously reported on the theoretical validity of FCAT performance outcomes as a predictive metric. However, only the FCAT performance levels were useful in logistic regression due to the reported inconsistency during the normalization procedures for the development of scaled scores (Buck et al., 2001; McBride & Wise, 2001).

Attendance

The effects of absenteeism on the odds of course enrollment and achievement were considered.

Suspension

For this study, in tandem with attendance as a predictor, the total number of accumulated suspensions (external, internal, and alternative to external) was considered.

Demographic Variables

The demographic variables included were dichotomous variables for gender, SES (calculated from reported eligibility for free or reduced-price lunch plan), receipt of ESE services, and ELL status. For this study, categorical variables were useful to classify types of self-identified race as predictors.

Statistical Analyses

Logistic Regression

To explore each variable associated with enrollment outcomes, a logistic regression model was employed utilizing the entire range of cases for enrollment (N = 12,102). Likewise, to explore each variable associated with chemistry course achievement, logistic regression was performed using the entire range of cases for chemistry achievement (n = 5,966). This approach was selected as the method of analysis because it allowed for the dependent variable in each trial to be evaluated as a discrete outcome (e.g., 0 = alternative science enrolled, 1 = chemistry enrolled; 0 = fail, 1 = pass). This allowed the logistic algorithm to determine the odds of cases falling into one or the other categories of the dependent variable as a function of the independent variables. Because of the dichotomous nature of the dependent variables, the relationship of the outcome to the predictors was not a linear condition (Cohen, Cohen, West, & Aiken, 2003). As such, to operationalization occurred as a sigmoid function (logit-link) as described by Cohen et al. (2003). Unless otherwise specified, the logistic regression models used a probability range from 0.0 to 1.0, with a cutoff value of .50. The classification odds of failure or success were considered as the odds of one outcome being in one of the two conditions, given multiple predictors (Cohen et al., 2003). The predictors for each academic discipline were the calculated GPA for that subject as previously described. Regarding demographic attributes, gender, SES, ESE, and ELL were all coded as dichotomous inputs (e.g., 0 = male and 1 = female). White non-Hispanics were set as the reference group for comparison. The total number of days a student was absent was coded as a continuous variable where both excused and unexcused absences were considered simultaneously. The rate of absenteeism was reported by the district relative to the total number of days enrolled. To control colinearity the total number of days externally suspended were subtracted from the total number of days absent (when applicable). The total number of days of suspension was considered as a continuous input and evaluated for a predictive contribution to the final model. The logit-linking function was employed through SPSS to calculate the natural logarithmic function of the odds of the outcome occurring as the predicted probability specified parameters of each logistic model (Cohen et al., 2003; Osborne, 2015).

Results

Power and Sample Size

A power analysis using G*Power determined that a sample of at least 250 cases was necessary to achieve a power of .95 for each iteration of logistic regression. The full ($N = 12{,}102$) and chemistry-enrolled subset ($n = 5{,}966$) datasets far exceeded the number of cases needed to satisfy the sample size parameters to have adequate power for the reported analysis.

Missing Data and EM Analysis

First, given the sheer percentage of sixth-graders whom did not enroll in an art course (representing 70% of missing data for this discipline) the variable was eliminated from further consideration. As previously mentioned, missing data was estimated as needed for the following academic predictors: mathematics, English, history, science, or FCAT achievement level were replaced with expectation maximization (EM)-generated values. Little's (1988) missing completely at random (MCAR) test demonstrated that the data were not missing completely at random ($p < .001$). The current study employed EM replacement because, when using archived student records, it is a reasonable expectation for some data to be missing by semester for some academic courses by student for any given discipline. One would not have a reasonable expectation for academic course data for an individual to be randomly missing values, for example, when students dis-enroll from a course of study, enroll in a course of study out of sequence, or earn partial credit for a course of study via non-traditional means (online virtual school or credit recovery). As can be seen in Table 2 the mean values included are virtually identical when missing data were either estimated or when cases were deleted list wise. Therefore, the dataset with estimated values was used for all subsequent analyses.

Demographics of the Sample and Correlational Analysis

Table 3 depicts the demographic distribution for the full range of cases ($N = 12{,}102$). Specifically, 50% of the students were female, 57% were considered low SES, 11% received ESE services, and 7% received ELL services. Table 4 depicts the results for the preliminary correlational analysis to determine the strength of the relationship between the predictors for the full range of cases ($N = 12{,}102$) across all variables. Although most predictors were affirmed to be significant, the correlation between prior academic achievement for mathematics, English, history, and science demonstrated a moderate relationship in connection with both enrollment and academic outcomes for chemistry course completion in 10th-grade.

Table 3. *Sixth-Grade Sample Demographic Distribution.*

Demographic	Frequency	%
Male	5,930	49
Female	6,172	51
English language learner	847	7
Free lunch	1,740	14
Reduced-price lunch	1,102	9
Free direct meals	4,070	33
Orthopedically impaired	8	< 1
Speech impaired	13	< 1
Language impaired	33	< 1
Deaf or hard of hearing	26	< 1
Visually impaired	6	< 1
Emotional/behavioral disability	117	< 1
Specific learning disability	999	8
Autism spectrum disorder	21	< 1
Traumatic brain injured	3	< 1
Other health impaired	79	< 1
Intellectual disability	12	< 1
Black	2,420	20
Hispanic	3,873	32
Non-Hispanic	847	7
White	4,962	41

Note. N = 12,102.

Predicting Enrollment in 10th-grade Chemistry

Research Question 1

Does academic achievement—as measured by course-letter grades earned for sixth-grade mathematics, English literacy, history, science, and FCAT (achievement level) — accurately predict the proportion of students who enroll in chemistry or an equivalent science course in the 10th-grade?

The entry method for logistic regression was employed to predict science course enrollment outcomes (i.e., enrolled versus not enrolled) in the 10th-grade from sixth-grade predictors. Evaluation of the academic predictors occurred simultaneously for enrollment (see Table 5). Cohen's *d* was calculated following Sánchez-Meca et al.'s (2003) recommendations. Prior academic achievement moderately forecast the outcome for enrollment while controlling for demographic attributes and suspension rates with 80.6% classification accuracy. The Nagelkerke pseudo-R^2 value was .535 for the full range of cases (N = 12,102). The t-ratio criterion for each predictor demonstrated that each significantly contributed to predicting the enrollment outcome (see Table 5). In summary, this model was able to identify sixth-grade students whom subsequently enrolled in chemistry or an alternative science with 80.6% accuracy.

Table 4. *Correlations Among all Variables in this Study.*

Predictor	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. Gender	—																		
2. SES	.0	—																	
3. ELL	.0**	.2*	—																
4. ESE	-.1*	.1*	.0	—															
5. Black	.0	.2*	-.1*	.1*	—														
6. White	.0	-.4*	-.3*	.0*	-.4*	—													
7. Hispanic	.0	.3*	.4*	.0	-.3*	-.6*	—												
8. Non-Hispanic	.0	.3*	.4*	.0	-.4*	-.6*	-.4*	—											
9. Absence	-.1*	.2*	-.1*	.2*	.1*	-.0*	.0*	.0*	—										
10. Suspension	-.1*	.2*	.0	.1*	.2*	-.1*	-.0*	-.0*	.3*	—									
11. Math	.2*	-.3*	-.1*	-.1*	-.2*	.2*	-.1*	.2*	-.3*	-.3*	—								
12. English	.2*	-.3*	-.1*	-.2*	-.2*	.2*	-.1*	-.1*	-.3*	-.3*	.7*	—							
13. History	.2*	-.3*	-.1*	-.2*	-.2*	.2*	-.1*	-.1*	-.3*	-.3*	.7*	.7*	—						
14. Science	.2*	-.3*	-.1*	-.2*	-.2*	.2*	-.1*	-.2*	-.3*	-.3*	.7*	.7*	.7*	—					
15. FCAT math	.0	-.3*	-.3*	-.2*	-.2*	.3*	-.1*	-.2*	-.2*	-.2*	.5*	.4*	.5*	.4*	—				
16. FCAT reading	.1*	-.4*	-.3*	-.2*	-.2*	.3*	-.2*	-.3*	-.2*	-.2*	.4*	.4*	.5*	.4*	.7*	—			
17. Science[1]	-.1*	.3*	.2*	.2*	.2*	-.2*	.1*	.1*	.1*	.1*	-.4*	-.4*	-.4	-.4*	-.5*	-.5*	—		
18. Chemistry[2]	.1*	-.2*	-.2*	-.2*	-.2*	.2*	-.1*	-.1*	-.1*	-.2*	.4*	.4*	.4*	.4*	.5*	.5*	-.8*	—	
19. Pass Chemistry	.1*	-.3*	-.2*	-.2*	-.2*	.2*	-.1*	-.1*	-.2*	-.1*	.4*	.4*	.4*	.4*	.4*	.4*	-.7*	.8*	—

Note. N = 12,102. SES = socioeconomic status; ELL = English language learner; ESE = exceptional student education; FCAT = Florida Comprehensive Assessment Test. All variables were measured in sixth-grade, except the last three variables which were measured in 10th-grade. [1]Alternative to chemistry science course enrollment; [2] Chemistry enrollment; $**p < .05$, two-tailed. $*p < .01$, two-tailed. All values rounded to one significant figure.

Table 5. *Sixth-Grade Logistic Model Predicting 10th-Grade Chemistry Course Enrollment, Controlling for Behavioral and Demographic Variables.*

Predictor	*B* (*SE*)	*t* ratio	Odds ratio	Cohen's *d*	% ΔR^2
Math	.195 (.051)	3.823***	1.215	.107	2
English	.314 (.051)	6.157***	1.368	.173	5
History	.293 (.054)	5.426***	1.341	.162	6
Science	.193 (.056)	3.446***	1.213	.106	2
FCAT math	.775 (.048)	16.146***	2.171	.427	38
FCAT reading	.694 (.048)	14.458***	2.002	.383	29

Note. N = 12,102. FCAT = Florida Comprehensive Assessment Test. Model classification accuracy = 80.6%; model Nagelkerke R^2 = .535. Change in Nagelkerke R^2 was calculated as the difference in percentage of variance between the models with the predictor minus the model without the predictor. ***$p <$ .001.

Research Question 2

Do student characteristics (gender, race, SES, ESE and/or ELL status) uniquely predict chemistry enrollment after controlling for the effects of sixth-grade academic achievement and FCAT subtest level?

Table 6. *Sixth-Grade Logistic Modeling for Demographics Predicting 10th-Grade Course Enrollment, While Already Controlling for Prior Sixth-Grade Achievement.*

Predictor	*B* (*SE*)	*t* ratio	Odds ratio	Cohen's *d*	% ΔR^2
Gender	.056 (.037)	1.513	1.058	.031	1
SES	-.190 (.040)	4.750***	.827	-.105	3
ELL	-.150 (.053)	2.830*	.861	-.080	1
ESE	-.166 (.032)	5.187***	.847	-.092	4
Black	.043 (.167)	.257	1.044	.024	0
Hispanic	.185 (.161)	1.150	1.203	.102	0
Non-Hispanic	.006 (.178)	.033	1.033	.018	0
White	.002 (.158)	.013	1.002	.001	0

Note. N = 12,102. SES = socioeconomic status; ELL = English language learner; ESE = exceptional student education. Model classification accuracy = 80.8%; model Nagelkerke R^2 = .544. Change in Nagelkerke R^2 was calculated as the difference in percentage of variance between the models with the predictor minus the model without the predictor. White = reference category. *$p < .05$, ***$p < .001$.

Table 6 depicts the results for the standardized demographic predictors, controlling for academic and FCAT achievement effects on the dichotomous outcome for chemistry compared to alternative science course enrollment for the full range of cases. As can be seen in Table 6, neither gender nor race had any significant predictive power in classifying enrollment outcomes. Cohen's *d* was calculated following Sánchez-Meca et al.'s (2003) recommendations. However, the *t*-ratio criterion demonstrated a negligible contribution to model classification accuracy when considering SES, where the change in Nagelkerke pseudo-R^2 value was only observed to change by .3. Thus, students who demonstrated greater socioeconomic vulnerability were .827 times less likely to enroll in chemistry courses when compared to students with greater measures of affluence. Likewise, the evaluation of indicators of ESE services demonstrated a weak, negative, significant contribution to model classification accuracy. Specifically, students who received ESE services were .847 times less likely to enroll into a chemistry course than their peers not receiving ESE services (see Table 6). Similarly, students who received ELL services were .867 times less likely to have a positive enrollment outcome, as can be seen in Table 6. Though individual predictors indicated some weak significant influence on enrollment (particularly for SES and ESE/ELL), overall this model was not able to accurately classify enrollment solely on totality of demographic attributes.

Research Question 3

Does absenteeism and/or number of suspensions in the sixth-grade uniquely predict 10th-grade chemistry enrollment after controlling for course academic course achievement, FCAT mathematics and reading achievement levels, and student characteristics?

Table 7 depicts the results for the absenteeism predictor and independently for suspension rates after controlling for academic and demographic inputs for the full range of cases. Neither the absenteeism nor the frequency of suspensions in sixth-grade made any significant contribution to model accuracy in predicting chemistry enrollment outcomes.

Table 7. *Logistic Models Considering Sixth-Grade Absenteeism and Suspensions Predicting Course Enrollment, While Already Controlling for Demographic Variables and Sixth-Grade Academic and Florida Comprehensive Assessment Test Achievement.*

Predictor	*B* (*SE*)	*t* ratio	Odds ratio	Cohen's *d*	% ΔR^2
Absenteeism sixth-grade	-.053 (.041)	1.293	.948	-.029	0
Suspension sixth-grade	-.070 (.049)	1.428	.933	-.038	0

Note. N = 12,102. No slopes and intercepts were significant at $p < .05$. Change in Nagelkerke R^2 was calculated as the difference in percentage of variance between the models with the predictor minus the model without the predictor.

Predicting Passing 10th-Grade Chemistry

Research Questions 4

Do sixth-grade course-letter grades for mathematics, English literacy, history, science, and FCAT achievement level accurately predict the proportion of students who pass chemistry (with a "C" or higher) in the 10th-grade?

From sixth-grade achievement levels, after controlling for absenteeism, demographics, and suspension rates an accurate prediction could be made with respect to passing or failing 10th-grade chemistry. Table 8 depicts the outcomes that were modeled with a classification accuracy of 94% and a Nagelkerke pseudo-R^2 of .214 (n = 5,966) for the sixth-grade achievement predictors.

Research Question 5

Do student characteristics (gender, race, SES, ESE/ELL) uniquely predict passing chemistry in the 10th-grade while controlling for the academic achievement and standardized test scores?

The demographic predictors were evaluated simultaneously while controlling for prior achievement, absenteeism, and suspension predictors. The *t*-ratio criterion demonstrated a significant contribution to model accuracy for both gender and SES. Female students were more likely than male students to pass chemistry with a letter grade of C or better. Regarding socioeconomically vulnerable students, obtaining a letter grade of C or better in chemistry was .739 times less likely to occur (see Table 9). As was observed with enrollment, for achievement, race was not a decisive factor in the odds of passing chemistry. Receipt of ESE services was not significant in affecting the odds of passing 10th-grade chemistry.

Though individual predictors indicated some significant influence on achievement particularly for SES and gender, overall this model was not able to accurately classify achievement solely on the totality of demographic attributes note the negligible gain in pseudo-R^2 value reported in Table 9.

Table 8. *Sixth-Grade Logistic Regression Models Predicting 10th-Grade Chemistry Course Achievement Considering Academic Predictors.*

Predictor	*B* (*SE*)	*t* ratio	Odds ratio	Cohen's *d*	% ΔR^2
Math	.466 (.075)	6.213***	1.593	.257	16
English	.137 (.075)	1.827	1.147	.076	1
History	.177 (.079)	2.240*	1.194	.098	2
Science	.346 (.080)	4.325***	1.414	.191	7
FCAT math	.245 (.066)	3.712***	1.278	.135	5
FCAT reading	.132 (.068)	1.941	1.141	.073	1

Note. N = 5,966. FCAT = Florida Comprehensive Assessment Test. Model classification accuracy = 94%; model Nagelkerke R^2 = .214. Change in Nagelkerke R^2 was calculated as the minuend of the standardized variables, entered simultaneously, less the subtrahend of the saturated model singularly controlling for the variable of interest.*$p < .05$. ***$p < .001$.

Table 9. *Sixth-Grade Logistic Modeling Predicting 10th-Grade Chemistry Course Achievement Considering Demographics While Already Controlling for Academic and Florida Comprehensive Assessment Test Achievement.*

Predictor	*B* (*SE*)	*t* ratio	Odds ratio	Cohen's *d*	% ΔR^2
Gender	.255 (.049)	5.204***	1.290	.140	11
SES	-.303 (.053)	5.717***	.739	-.167	13
ELL	.132 (.095)	1.389	1.389	.073	1
ESE	-.051 (.047)	1.085	.950	-.028	1
Black	-.074 (.220)	.336	.928	-.041	0
Hispanic	-.123 (.204)	.603	.884	-.068	0
Non-Hispanic	-.135 (.209)	.767	.865	-.080	0
White	-.035 (.199)	.176	.965	-.020	0

Note. N = 5,966. SES = socioeconomic status; ELL = English language learner; ESE = exceptional student education. Model classification accuracy = 76.7%; model Nagelkerke R^2 = .243. Change in Nagelkerke R^2 was calculated as the difference in percentage of variance between the models with the predictor minus the model without the predictor. White = reference category. ***$p < .001$.

Research Question 6

Do student absences or number of suspensions in sixth-grade uniquely predict passing chemistry in the 10th-grade while controlling for the effects of prior grades, standardized test scores, and student characteristics?

The standardized predictors for absenteeism and, independently, suspensions were evaluated while controlling for prior academic achievement and demographic predictors for the effect chemistry achievement outcomes for the full range of cases (n = 5,966). Neither the rate of absenteeism nor the frequency of suspensions in sixth-grade made any significant contribution to model accuracy in predicting chemistry enrollment outcomes (see Table 10).

Table 10. *Logistic Regression Considering Sixth-Grade Absenteeism and Suspension Predictors for 10th-Grade Chemistry Course Achievement, While Already Controlling for Demographics, and Sixth- Grade Academic and Florida Comprehensive Assessment Test Achievement.*

Predictor	*B* (*SE*)	*t* ratio	Odds ratio	Cohen's *d*	% ΔR^2
Absenteeism sixth-grade	-.086 (.060)	1.433	.918	-.047	1
Suspension sixth-grade	-.004 (.089)	.045	.996	-.002	0

Note. N = 5,966. ELL = English language learner; ESE = exceptional student education. No slopes and intercepts were significant at $p < .05$. Change in Nagelkerke R^2 was calculated as the difference in percentage of variance between the models with the predictor minus the model without the predictor.

Discussion

Of the theoretical frameworks proposed, the data supports the first view. The first view postulated that the level of prior achievement in mathematics and/or science in sixth-grade is key to future success. In this way, success acts as a bottleneck for pathways into chemistry and serves as an impediment to future achievement (see Figure 1). Data depicted in Table 8 supports the importance of sixth-grade course achievement in mathematics and science on the likelihood of chemistry course achievement. Regarding results pertaining to enrollment, female students were more likely to enroll in chemistry than male students. These findings are consistent with prior research, which has suggested that the gender gap previously reported in the sciences has narrowed over the course of the last decade (Ellison & Swanson, 2010; Goldin, Katz, & Kuziemko, 2006; Jacobs, 2005; Legewie & DiPrete, 2014).

Considering other demographic attributes, SES certainly stands out and has long been an area of research focus. Thus, a large body of evidence has suggested that socioeconomic vulnerability is still associated with diminished access to resources, which has overt and latent effects on learning outcomes, especially among students at or below the poverty line (Lorah & Ndum, 2013; Sirin, 2005). In the context of this study, students with higher socioeconomic vulnerability were indeed less likely to enroll in chemistry courses than their more affluent peers. Race did not significantly contribute to the overall classification accuracy and did not significantly account for variance in the model. Eligibility for and/or receipt of ESE or ELL services in the sixth-grade each diminished the likelihood of enrollment, which is also consistent with previous research (Klingner, Vaughn, Hughes, Schumm, & Elbaum, 1998). In practice, students with special learning needs (with the exception of gifted students) require more core and remedial coursework; thus, student schedules imbued with specific course to serve the needs of ESE or ELL students may reduce their availability to enroll in a course that is not currently a graduation requirement. This may, in part, explain lower chemistry enrollment among ESE and ELL students in this study.

Regarding results pertaining to achievement, high school outcomes are moderated by chronic absenteeism (MacIver & Messel, 2012) and suspensions (Myers, Milne, Baker, & Ginsburg (1987). In this study, neither rate of absenteeism nor number of suspensions in the sixth-grade made a significant contribution to predicting enrollment outcomes. Though the rate of absenteeism and number of suspensions did not contribute to the overall modeled enrollment outcome, both variables may have more immediate or direct individual effects. These effects may be more pronounced at a temporal point more proximal to the outcome. Also, frequent suspensions and chronic absenteeism are likely the exception rather than the norm. In this study,

75% of students in the cohort were absent 12 days or less, and 90% were suspended for 3 days or less. In this light, neither the absenteeism nor the suspension predictors would be expected to have any discernable effect on the enrollment outcome. This is because the temporal point investigated was five years predating the outcome. Future investigations should explore the subset of 10th-grade students who were identified as missing more than 12 days of school or were suspended for more than 3 days for the effects on chemistry outcomes (beyond the scope of this study).

Cumulative sixth-grade course grades, particularly in the case of math and science course outcomes, significantly contributed to predictive modeling outcomes, while controlling for standardized FCAT achievement, absenteeism, demographic, and suspension variables. In general, prior achievement in mathematics and science was a particularly important factor for chemistry course enrollment, which is consistent with the literature. Interestingly, when considering FCAT achievement while controlling for all other variables, the FCAT achievement levels were the best indicator of the likelihood of course enrollment in the 10th-grade. In contrast, FCAT achievement was inferior to prior academic proficiency in predicting chemistry achievement outcomes.

Conclusion

The reported findings of this study bridge the gap in the prior literature that focuses on postsecondary chemistry outcomes. Our study provides the first rigorous and comprehensive analysis of the strength of relations between several middle school variables and secondary chemistry outcomes. The current findings should be considered along with research such as that reported by Harachiewicz, Barron, Tauer, and Elliot (2002) that document the high predictability of high school performance on both the short- and long-term academic success in postsecondary education. More recently, Ayan and Garcia (2008) confirmed Harachiewicz et al.'s findings, particularly for postsecondary chemistry. Further, our support of the first alternative model, adds to the growing body of evidence indicating that prior course achievement, especially math and science coursework, is strongly predictive of future achievement in high school (Duncan et al., 2007; Hemmings et al., 2011; House et al., 1996; McKenzie & Schweitzer, 2001; Watts et al., 2014; Zeegers, 2004). School districts should employ findings, such as presently reported, as part of their strategic efforts to improve both enrollment and achievement in high school chemistry.

References

ACT. (2011). *The forgotten middle: Ensuring that all students are on target for college and career readiness before high school.* Retrieved from http://www.act.org/content/dam/act/unsecured/documents/ForgottenMiddleSummary.pdf

Ayan, M. N., & Garcia, M. T. (2008). Prediction of university students' academic achievement by linear and logistic models. *Spanish Journal of Psychology, 11*, 275–288. doi:10.1017/S1138741600004315

Balfanz, R., & Byrnes, V. (2009). Closing the mathematics achievement gap in high- poverty middle schools: Enablers and constraints. *Journal of Education for Students Placed at Risk, 11*, 143–159. doi:10.1207/s15327671espr1102

Balfanz, R., Herzog, L., & MacIver, D. J. (2007). Preventing student disengagement and keeping students on the graduation path in urban middle-grades schools: Early identification and effective interventions. *Education Psychologist*, *42*, 223–235. doi:10.1080/00461520701621079

Bloom, H. S., Hill, C. J., Black, A. R., & Lipsey, M. W. (2008). Performance trajectories and performance gaps as achievement effect-size benchmarks for educational interventions. *Journal of Research on Educational Effectiveness, 1*, 289–328. doi:10.1080/19345740802400072

Bodovski, K., Nahum-Shani, I., & Walsh, R. (2013). School climate and students' early mathematics learning: Another search for contextual effects. *American Journal of Education, 119*, 209–234. doi:10.1086/667227

Borden, V. M., & Young, J. W. (2008). Measurement validity and accountability for student learning. *New Directions for Institutional Research, 9*(1), 19–37. Doi: 10.1002/ir.259

Buck, J., Torgesen, J., & Schatschneider, C. (2001). *Predicting FCAT-SSS scores using prior performance on the FCAT-SSS, FCAT-NRT, and SAT9*. Tallahassee: Florida Center for Reading Research.

Chambers, K. A. (2005). *Improving performance in first year chemistry* (Doctoral dissertation). Available from ProQuest Dissertations & Theses database. (UMI No. 3326512)

Chen, X., & Ho, P. (2012). *STEM in postsecondary education: Entrance, attrition, and course-taking among 2003–2004 beginning postsecondary students* (NCES 2013- 152). Washington, DC: National Center for Education Statistics. Retrieved from http://nces.ed.gov/pubsearch/pubsinfo.asp?pubid=2013152

Chen, X., & Soldner, M. (2013). *STEM attrition: College students' paths into and out of STEM fields* (NCES 2014-001). Washington, DC: National Center for Education Statistics. Retrieved from http://nces.ed.gov/pubs2014/2014001rev.pdf

Christian, B., & Yezierski, E. (2012). A change for chemistry. *Science Scope, 35*(8), 60–65. Retrieved from http://www.nsta.org/middleschool/

Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2003). *Applied multiple regression and correlation analysis fort the behavioral sciences* (3rd ed.). Mahwah, NJ: Sage.

Cokelez, A. (2012). Junior high school students' ideas about the shape and size of the atom. *Research in Science Education, 42*, 673–686. doi:10.1007/s11165-011-9223-8

Cooper, C. I., & Pearson, P. T. (2012). A genetically optimized predictive system for success in general chemistry using a diagnostic algebra test. *Journal of Science Education and Technology, 21*, 197–205. doi:10.1007/s10956-011-9318-z

Craney, C. L., & Armstrong, R. W. (1985). Predictors of grades in general chemistry for allied health students. *Journal of Chemical Education, 62,* 127–129. doi:10.1021/ed062p127

Dong, Y., & Peng, J. C. (2013). Principled missing data methods for researchers. *Journal of Methodology, 2*(222). doi:10.1186/2193-1801-2-222

Duncan, G. J., Claessens, A., Huston, A. C., Pagani, L. S., Engel, M., Sexton, H., & Japel, C. (2007). School readiness and later achievement. *Developmental Psychology, 43*, 1428– 1446. doi:10.1037/0012-1649.43.6.1428

Eagan, K., Hurtado, S., Figueroa, T., & Hughes, B. (n.d.). *Examining STEM pathways among students who begin college at four-year institutions.* Los Angeles: University of California. Retrieved from http://sites.nationalacademies.org/cs/groups/dbassesite/documents/webpage/dbasse_088834.pdf

Easter, D. C. (2010). Factors influencing student prerequisite preparation for and subsequent performance in College Chemistry Two: A statistical investigation. *Journal of Chemical Education, 87*, 535–540. doi:10.10021ed800165t

Ellison, G., & Swanson, A. (2010). The gender gap in secondary school mathematics at high achievement levels: Evidence from the American mathematics competitions. *Journal of Economic Perspectives, 24*, 109–128. doi:10.1257/jep.24.2.109

Florida Board of Governors Regulations. (2016). *Rule 6.002: Admission of undergraduate first-time-in-college, degree seeking freshmen.* Retrieved from http://www.flbog.edu/documents_regulations/regulations/6%20002%20Admission%20of%20Undergraduate%20FTIC%20Frehsmen%20%28mv%20edits%29.pdf

Florida Department of Education. (2013). *FCAT handbook: A resource for educators*. Retrieved from http://fcat.fldoe.org/handbk/complete.pdf

Florida Department of Education (2014). *FCAT 2.0 and Florida EOC assessment achievement levels.* Retrieved from http://www.fldoe.org/core/fileparse.php/3/urlt/achlevel.pdf

Gardner, D. P, Larsen, Y. W., Baker, W., Campbell, A., & Crosby, E. A. (1983). *A nation at risk: the imperative for education reform* (p. 65). United States Department of Education.

Gasiewski, J., Eagan, K., Garcia, G., Hurtado, S., & Chang, M. J. (2011). From gatekeeping to engagement: A multi-contextual, mixed method study of student academic engagement in introductory STEM courses. *Research in Higher Education, 53*, 229– 261. doi:10.1007/s11162-011-9247y

Geiser, S., & Santelices, M. V. (2007, June). Validity of high-school grades in predicting student success beyond the freshman year: High school record vs. standardized test as indicators of four-year college outcomes. Berkeley: University of California, Center for Studies in Higher Education. Retrieved from http://www.cshe.berkeley.edu/publications/validity-high-school-grades-predicting-student-success-beyond-freshman-yearhigh-school

Goenner, C. F., & Snaith, S. M. (2004). Accounting for model uncertainty in the prediction of university graduation rates. *Research in Higher Education, 45*, 25– 41. doi:10.1023/B:RIHE.0000010045.13366.a6

Goldin, C., Katz, L. F., & Kuziemko, I. (2006). The homecoming of American college women: The reversal of the college gender gap. *Journal of Economic Perspectives, 20*, 133–156. doi:10.1257/jep.20.4.133

Grosset, J. M., & Hawk, T. R. (1986, June). *Construction and application of a socio- economic status variable.* Paper presented at the Annual Forum of the Association for Institutional Research, Orlando, FL. Retrieved from ERIC database. (ED280403)

Gu, X., Solomon, M. A., Zhang, T., & Xiang, P. (2011). Group cohesion, achievement motivation, and motivational outcomes among female college students. *Journal of Applied Sport Psychology, 23,* 175–188. doi:10.1080/10413200.2010.548847

Gullo, D. F. (2013). Improving instructional practices, policies, and student outcomes for early childhood language and literacy through data-driven decision making. *Early Childhood Education Journal, 41*, 413–421. doi:10.1007/s10643-013-0581-x

Guthrie, J. T., & Davis, M. H. (2010). Motivating struggling readers in middle school through an engagement model of classroom practice. *Reading and Writing Quarterly: Overcoming Learning Difficulties, 19*, 59-85. doi:10.1080/10573560308203

Harachiewicz, J. M., Barron, K. E., Tauer, J. M., & Elliot, A. J. (2002). Predicting success in college: A longitudinal study of achievement goals and ability measures as predictors of interest and performance from freshman year through graduation. *Journal of Education Psychology, 94*, 562–575. doi:10.1037/0022-0663.94.3.562

Hauptli, M. V., & Cohen-Vogel, L. (2013). The federal role in adolescent literacy from Johnson through Obama: A policy regimes analysis. *American Journal of Education, 119*, 373– 404. doi:10.1086/669852

Hayali, T. (2013). *The influence of high school academics on freshman college mathematics and science courses at SUNY Oswego* (Doctoral dissertation). Available from ProQuest Dissertations & Theses database. (UMI No. 3575413)

Hemmings, B., Grootenboer, P., & Kay, R. (2011). Predicting mathematics achievement: The influence of prior achievement and attitudes. *International Journal of Science and Mathematics Education, 9*, 691–705. doi:10.1007/s10763-010-9224-5

House, J. D., Hurst, R. S., & Keely, E. J. (1996). Relationship between learner attitudes, prior achievement, and performance in a general education course: A multi- institutional study. *International Journal of Instructional Media, 23*, 257–271. Retrieved from ERIC database. (EJ569021)

Jacobs, J. E. (2005). Twenty-five years of research on gender and ethnic differences in math and science career choices: What have we learned? *New Directions for Child and Adolescent Development, 110*, 85–94. doi:10.1002/cd.151

Johnson, W. L., Johnson, A. M., & Johnson, J. (2012). *Predicting student success on the Texas chemistry STAAR test: A logistic regression analysis.* Retrieved from ERIC database. (ED534647)

Kim, D. Y., Zabel, J. E., Stiefel, L., & Schwartz, A. E. (2006). School efficiency and student subgroups: Is a good school good for everyone? *Peabody Journal of Education, 81*, 95– 117. doi:10.1207/s153279300pje8104-5

Klingner, J. K., Vaughn, S., Hughes, M. T., Schumm, J. S., & Elbaum, B. (1998). Outcomes for students with and without learning disabilities in inclusive classrooms. *Learning Disabilities Research and Practice*, *13*, 153–161. Retrieved from http://www.colorado.edu/UCB/AcademicAffairs/educaiton/faculty/janetteklinger/Docs/Klinger et al_Outcomes for Students.pdf

Kobrin, J. L., Patterson, B. F., Shaw, E. J., Mattern, K. D., & Barbuti, S. M. (2008). *Validity of the SAT for the predicting of first-year college grade point average* (Research Report No. 2008-5). New York, NY: The College Board. Retrieved from https://research.collegeboard.org/programs/sat/data/validity-studies

Laird, J., Alt, M., & Wu, J. (2009). *STEM coursetaking among high school graduates, 1990–2005.* Berkeley, CA: MPR. Retrieved from http://www.rti.org/publication/stem-course-taking-among-high-school-graduates- 1990-2005

Lebihan, L., & Takogmo, C.-O. M. (2015). *Academic achievement trajectories and risk factors during early childhood* (Publication No. 2015s-47). Québec, Canada: Cirano. Retrieved from http://www.cirano.qc.ca/files/publications/2015s-47.pdf

Legewie, J., & DiPrete, T. A. (2014). The high school environment and the gender gap in science and engineering. *Sociology of Education, 87*, 259–280. doi:10.1177/0038040714547770

Little, R.J.A. (1988). A test of missing completely at random for multivariate data with missing values. Journal of the American Statistical Association, 83(404), 1198- 1202. doi: 10.1080/01621459.1988.10478722

Lorah, J., & Ndum, E. (2013). *Trends in achievement gaps in first-year college courses for racial/ethnic, income, and gender subgroups: A 12-year study.* Iowa City, IA: ACT.

Luxford, C. J., & Bretz, S. L. (2014). Development of the Bonding Representations Inventory to identify student misconceptions about covalent and ionic bonding representations. *Journal of Chemical Education, 91*, 312–320. doi:10.1021ed400700q

MacIver, M. A., & Messel, M. (2012). *Predicting high school outcomes in the Baltimore City Public Schools. Senior Urban Education Research Series, Vol. 7.* Washington, DC: Council of the Great City Schools. Retrieved from ERIC database. (ED536739)

Maki, P. L. (2004). *Assessing for learning: Building a sustainable commitment across the institution*. Herndon, VA: Stylus.

McBride, J., & Wise, L. (2001). *Developing a vertical scale for the Florida Comprehensive Assessment Test (FCAT).* Retrieved from http://fcat.fldoe.org/pdf/devVertScaleFCAT.pdf

McKenzie, K., & Schweitzer, R. (2001). Who succeeds at university? Factors predicting academic performance in first year Australian university students. *Higher Education Research & Development, 20*, 21–33. doi:10.1080/07924360120043621

Myers, D. E., Milne, A. M., Baker, K., & Ginsburg, A. (1987). Student discipline and high school performance. *Journal of Sociology of Education, 60*, 18–33. doi:10.2307/2112616

National Center for Education Statistics. (2012). *STEM in postsecondary education: Entrance, attrition, and course taking among 2003-2004 beginning postsecondary students* (NCES 2013-152). Retrieved from http://nces.ed.gov/pubs2013/2013152.pdf

Newman, M. (2013). Emergence, supervenience, and introductory chemical education. *Science & Education, 22*, 1655–1667. doi:10.1007/s11191-012-9441-0

Nizoloman, O. N. (2013). Relationship between mathematical ability and achievement in mathematics among female secondary school students in Bayelsa State Nigeria. *Social and Behavioral Sciences*, *106*, 2230–2240. doi:10.1016/j.sbspro.2013.12.254

Noble, J. P., & Sawyer, R. (1987). *Predicting grades in specific college freshman courses from ACT test scores and self-reported high school grades* (ACT Research Report No. 87-20). Retrieved from http://www.act.org

Noble, J. P., & Sawyer, R. (2002). *Predicting different levels of academic success in college using high school GPA and ACT composite score* (ACT Research Report No. 2002-4). Retrieved from http://www.act.org

Nonis, S. A., & Wright, D. (2003). Moderating effects of achievement striving and situational optimism on the relationship between ability and performance outcomes of college students. *Research in Higher Education, 44*, 327–346. doi:10.1023/A:1023029815944

Nordstrom, B. H. (1990, April). *Predicting performance in freshman chemistry*. Paper presented at the National Meeting of the American Chemical Society, Boston, MA.

Obrentz, S. B. (2012). *Predictors of science success: The impact of motivation and learning strategies on college chemistry performance* (Doctoral dissertation). Available from ProQuest Dissertations & Theses database. (UMI No. 3501091) Osborne, J. W. (2015). *Best practices in logistic regression*. Thousand Oaks, CA: Sage.

Pugh, C. M., & Lowther, S. (2004). *College math performance and last high school math course*. Retrieved from Auburn University, Office of Institutional Research and Assessment website: https://oira.auburn.edu/about/publications/SAIRPaper2004.pdf

Ramful, A., & Narod, F. B. (2014). Proportional reasoning in the learning of chemistry: Levels of complexity. *Mathematics Education Research Journal, 26*, 25–46. doi:10.1007/s13394-13-110-7

Sadler, P. M., & Tai, R. H. (2000). Success in introductory college physics: the role of high school preparation. Science Education, 85(2), 11 – 136. doi: 10.1002/1098- 237X(200101)

Sánchez-Meca, J., Marín-Martínez, F., & Chacón-Moscoso, S. (2003). Effect-size indices for dichotomized outcomes in meta-analysis. *Psychological Methods, 8*, 448–467. doi:10.1037/1082-989X.8.4.448

Sawyer, R. (2010). *Usefulness of high school average and ACT scores in making college admission decisions* (ACT Research Report No. 2010-2). Iowa City, IA: ACT. Retrieved from ERIC database. (ED527216)

Scafidi, T., & Bui, K. (2010). Gender similarities in math performance from middle school through high school. *Journal of Instructional Psychology, 37*, 252–255. Retrieved from ERIC database. (EJ952129)

Seery, M. K. (2009). The role of prior knowledge and student aptitude in undergraduate performance in chemistry: A correlation-prediction study. *Journal of Chemistry Education, 10*, 227–232. doi:10.1039/b9145402h

Sirin, S. R. (2005). Socioeconomic status and academic achievement: A meta-analytic review of research. *Educational Research, 75*, 417–453. doi:10.3102/00346543075003417

Useem, E. L. (2010). Student selection into course sequences in mathematics: The impact of parental involvement and school policies. *Journal of Research on Adolescence*, *1*, 231– 250. doi:10.1207/s15327795jra0103_3

Vigdor, J. L. (2012). *Solving America's mathematics education problem.* Retrieved from the American Enterprise Institute website: http://www.aei.org/wp- content/uploads/2012/08/-solving-americas-mathematics-education-problem_085301336532.pdf

Wagner, E. P., Sasser, H., & Dibiase, W. J. (2002). Predicting students at risk in general chemistry using pre-semester assessments and demographic information. *Journal of Chemical Education, 79*, 749–755. doi:10.1021ed079p749

Walford, E. T. (1983). High school chemistry: preparation for college or preparation for life? *Journal of Chemistry Education. 60*(12), 1053-1055. doi: 10.1021/ed060p1053

Wang, J., & Goldschmidt, P. (2010). Importance of middle school mathematics on high school students' mathematics achievement. *Journal of Educational Research, 97*(1), 3–17. doi:10.1080/00220670309596624

Watts, T. W., Duncan, G. J., Siegler, R. S., & Davis-Kean, P. (2014). What's past is prologue: Relations between early mathematics knowledge and high school achievement. *Educational Researcher, 43*, 352–360. doi:10.31020013189x14553660

Wilson, K. M. (1983). *A review of research on the prediction of academic performance after the freshman year* (College Board Report No. 83-2). Retrieved from the College Board website: https://research.collegeboard.org/publications/content/2012/05/review-research-prediction-academic-performance-after-freshman-year

Worley, C. L. (2007). *At-risk students and academic achievement: The relationship between certain selected factors and academic success* (Doctoral dissertation). Retrieved from http://scholar.lib.vt.edu/

Zeegers, P. (2004). Student learning in higher education: A path analysis of academic achievement in science. *Higher Education Research and Development, 23*, 35–56. doi:10.1080/0729436032000168487

Zhou, X., & Lim, J. S. (2014). Replace missing values with EM algorithm based on GMM and naïve Bayesian. *International Journal of Software Engineering, 8*, 177–188. doi:10.14257/ijseia.2014.8.5.14

Zuidema, D. R., & Eames, K. J. (2014). Comparison of high school dual-enrollment and traditional first-term general/organic/biochemistry college chemistry class outcomes. *Journal of Chemical Education, 91*, 2058–2063. doi:10.1021/ed500516x

Corresponding Author:
Nathan Lee Charnock
Hillsborough County Public Schools
16550 Fishhawk Blvd.,
Lithia, FL 33547
E-mail: mailto:novembersigma@gmail.com