ELECTRONIC JOURNAL FOR RESEARCH
IN SCIENCE & MATHEMATICS EDUCATION
VOL. 27, NO. 2, 122-157

Predicting Preservice Teachers' Performance on the Science Core of the EC-6 TExES General Certification Examination

Ruthanne Thompson
University of North Texas

Naudin Alexis
University of North Texas

Pamela Esprivalo Harrell
University of North Texas

ABSTRACT

Predicting preservice teachers' performance on their certification examination may meaningfully help Educators Preparation Programs (EPPs) to adapt and integrate learning frameworks that can improve their passing rates. This study used multiple linear regression (MLR) and binomial logistic regression (BLR) to explore potential variables that may impact the preparedness of 170 pre-service teachers to pass the science core of the official EC-6 Texas Examinations for Educator Standards (TExES) certification examination. The study was conducted by issuing a practice EC-6 TExES certification examination in a pretest and post-test manner during the semester that the participating cohort were enrolled in BIOL 1082, a mandatory science course EC-6 preservice teachers need to take prior to the official state EC-6 TExES certification exam. Additionally, the cohort took an online Qualtrics™ survey that collected ex post facto and other demographics data. The independent variables explored in this study included: final grade in BIOL 1082, classification, transfer status, prior college science coursework, enrollment status, family's college history, and current GPA. The dependent variable used was the post-test score on the practice EC-6 exam. The independent variable, grade in BIOL 1082 was revealed to be the single best predictor of preservice teachers' performance on the science practice examination across both the MLR and BLR models. The BLR models had a higher prediction accuracy of preservice teachers who would most likely fail the practice test than those who may pass at a prediction rate at approximately 79% accuracy. Based on the 67 out of 170 preservice teachers who passed the post-test, the accuracy of predicting failures may be a useful tool that EPPs can use in identifying students who may be at risk of failing and thus implement necessary interventions and other educational strategies.

Keywords: preservice teachers, multiple linear regression, binomial logistic regression, predictor factors, certification

Introduction

Science and mathematics have long been considered the toughest subjects for students to master at the primary level through the tertiary level of education (Murphy & Smith, 2012; Pino-Pasternak &

Volet, 2018; van Aalderen-Smeets et al., 2017). The belief in preconceived poor performance in science have at times caused even the most brilliant of students to pivot to courses and degrees that were considered less challenging (Pino-Pasternak & Volet, 2018). The carried belief of mediocre performance in science at times has come from family members and for some students their low self-efficacy in science has come from their own teachers (Pino-Pasternak & Volet, 2018). Further, according to Murphy et al., (2007) many preservice teachers have themselves predicted that they will not perform well on the science portion of their certification examination. Additionally, some elementary classroom teachers, even after passing their certification examination, have expressed that they spend the least amount of time on the subject matter of science in the classroom (Binns et al., 2020). This cyclical apprehension of preservice teachers' ability to learn and teach science can in turn lead to their future students getting low exposure to science content, which can then be reflected as an ongoing lapse in students' commitment to persevere in learning science. Later, if these same students pursue teacher certification, they may unintentionally relay to their students that success in science is unachievable (Binns et al., 2020; Pino-Pasternak & Volet, 2018). Studies have also shown that a connection exists between the passing of the certification exam and a preservice teacher's effectiveness in the classroom (Boyd et al., 2007; Donovan et al., 2014; Senler, 2016).

In the state of Texas, to obtain an elementary teacher certification one must pass the Texas Examination for Educator Standards (TExES) Early Childhood to 6th grade (EC-6) examination (EC-6 TExES). Prior to 2015, students were allowed an unlimited number of attempts to pass the exam. After 2015, with the passing of the *EESA Act*, examinees are only allowed five attempts to pass the exam with a score of at least 80%. In tandem with this shift in the number of attempts allowed, the Educator Preparation Programs (EPPs) must also maintain an overall pass rate of 85% each year to meet accreditation requirements (Warren, 2017). Creating a model to predict preservice teachers' performance on their official certification examination may not only help boost a preservice teacher's motivation, self-efficacy, and confidence (Ebrahim, 2012), but may also serve as a beneficial tool to the EPPs (Hutson, 2017).

The TExES™ EC-6 certification examination consists of two subdivisions: content area for the specific grade level, and pedagogy and professional responsibilities (Feuer et al., 2013; Gard, 2011; Sasson, 2014). There are five subject domains within the content portion of the exam: Domain I: English Language Arts Reading, & the Science of Teaching Reading (28%); Domain II: Mathematics (18%); Domain III: Social Studies (16%); Domain IV: Sciences (19%); and Domain V: Fine Arts, Health, and Physical Education (19%) (TExES™ program preparation manual, 2019). This study focused on subject Domain IV: Sciences, which includes 18 competencies over which 52 multiple choice questions are asked on the official EC-6 TExES exam. The courses offered at the EPP prepare preservice teachers for the science portion of the EC-6 certification examination and include BIOL 1082 (Biology for Elementary Educators), BIOL 1132 (Environmental Science for non-science majors), GEOG 1710 (Earth Science for non-science majors), PHYS 1210 (Conceptual Physics for non-science majors), and EDEE 4330 (Science Methods for Elementary Educators). The Biology for Educators course (BIOL 1082) was developed exclusively for preservice Elementary Education majors and covers approximately 8 of the 18 competencies of Domain IV, which makes up about 44% of the science concepts that need to be mastered for the certification examination. The other three science courses, Environmental Science, Earth Science, and Conceptual Physics are also taught within the College of Science; however, these courses are open to all non-science majors and are not taught in context of becoming an elementary teacher. In their senior year, elementary education majors, take EDEE 4330, Science Methods, which is taught within the College of Education. Since Biology for Elementary Educators has content that covers material from the other three science courses and, as a single course, covers the largest amount of the material on the official examination (44%), it was selected as the focus for this study.

Predicting preservice teacher passing rates on the state certification examination and identifying potential variables that may influence their performance is beneficial to EPPs, preservice teachers themselves, and other agencies (Hutson, 2017). Various studies have explored the impact of academic and environmental factors that may influence students' performance on the teacher certification examination. Most studies have included academic factors such as GPA, familial influences, age, workload, full time or part-time status, and other environmental factors (DeFreitas & Rinn, 2013; Graunke & Woosley, 2005; Kim & Corcoran, 2018; Peters & Draughon, 2017; Swecker et al., 2013). Though studies have explored factors that may impact or predict performance on preservice teachers state certification examination, most of these studies looked at how preservice teachers performed on the overall content exam where all the subject areas were combined, or their performance was examined based on performance on the Pedagogy and Professional Responsibilities (PPR) with factors such as GPA, first-generation, and course grades predicting performance on the overall certification examination (Frizzell, 2014; Gard, 2011; Kazempour & Sadler, 2015; Kim & Corcoran, 2018; Warren, 2017).

Of the few studies that have explored preservice teachers' performance on individual subject matter exams, academic factors showed some correlation to predicted performance of preservice teachers on the certification examination. In previous studies, exploring predictors of performance on teacher certification examination, Gard (2011) investigated factors predicting failure on TExES 8-12 History and found that transfer status and GPA were closely correlated to success on the examination. Thobega and Miller (2008) explored factors predicting preservice teachers' performance in agriculture certification and revealed that ACT scores and gender were highly correlated to success on the PRAXIS II content examination. On the other hand, Sandholtz and Shea's (2015) exploration of preservice teachers' predicted performance in California state licensing revealed that grades in prerequisite courses as well as supervisors anticipated performance of preservice teachers were not accurate predictors of performance on certification examinations.

Further, the National Council on Teacher Quality (NCTQ) stated that almost half of EPPs do not analyze preservice teacher content knowledge before and after science courses, nor do they associate such coursework with predicted/actual performance on certification examinations (NCTQ, 2014). In fact, most of the previous studies exploring teacher certification examinations were in subject areas of mathematics or history or addressed the overall general content examination. In the single study that attempted to dissect the subject matter within the content area of EC-6 generalists (Bains, 2011), the trajectory of the study was to investigate the pass rate of each subject area. Thus far, no study has been identified that has exclusively explored the predictive modeling of preservice teachers' performance on the science portion of the content area of certification examinations. Thus, there remains a gap in the literature on investigating factors that may affect preservice teachers' performance on the individual subject domains within the EC-6 TExES content examination. With science being a subject matter that seems daunting to both preservice teachers and their future students, predicting performance of preservice teachers on science subject area (Domain IV) of the EC-6 TExES certification exam was targeted as the subject matter to be explored (Warren, 2017). Based on factors from previous studies and a class survey, variables showing correlation to students' performance were selected as independent variables and analyzed using multiple linear regression (MLR) and binomial logistic regression (BLR). Variables such as grades, transfer status, previous courses taken, credits taken, first-generation and relatives in education were identified using a survey. The outcome variable was the score on the science practice exam.

EPPs can lose their accreditation status and preservice teachers can accrue additional debt and lowered self-confidence if failure on the official EC-6 TExES certification exam occurs (Hutson, 2017). Additionally, the rigor for each certification examination has increased along with an increase in student population in all classes in every state (Darling-Hammond, 2019). The findings of this study may help guide EPPs on how and where to best utilize their resources to support preservice teachers prior to their taking of the official certification examination and may also help guide preservice teachers on which science competencies they need to most focus their remediation efforts. Additionally, predictive factors identified as having a potential impact on performance may be useful in the early part of the recruitment of preservice teachers into EPP programs. (Linn & Jacobs, 2015).

Literature Review

Learning and teaching science is still regarded as one of the most difficult tasks for preservice teachers to grasp (Hutson, 2017). In studies assessing preservice teachers' readiness to teach science in a classroom, approximately 70% of first-time classroom teachers expressed nervousness and unpreparedness to teach science in comparison to teaching the other subjects (Binns et al., 2020; Pino-Pasternak & Volet, 2018). Pre ESSA Act (2015), pre-service teachers could do extremely well in one subject area and that would compensate for doing poorly in another, so long as the overall score was passing. Post *ESSA* Act, minimal proficiency must be achieved in all subjects as each is scored separately and each must reach the 80% threshold. For this reason, having a solid knowledge on each of the 18 competencies for Domain IV is essential (Sawyers & Myers, 2018). Predictive factors that can influence preservice teachers' performance on their official certification examination can be a powerful tool used by EPPs to focus their attention and resources on the areas and factors to help in both the retention of enrollees within their program as well as improving the pass rate of their students (Warren, 2017). Preservice teachers that score at or below the required 80% on their practice examination can receive scaffolding and other types of interventions to help improve their scores on the official examination. Additionally, a predictive model can highlight the independent variables, both academic and environmental, that may predict actual performance.

Regression models have long been used to build predictive models, with multiple linear regression being the most used (Sullivan et al., 1996). In this study, both multiple linear regression, and binomial logistic regression models were used to predict performance. While a binomial logistic model can be employed to predict broad dichotomous outcomes such as *pass* or *fail*, multiple linear regression offers a closer estimation of the actual score. For instance, logistic regression can place individuals into a *pass* category, however the score could be 79.9%, which would be on the cusp of failing. Thus, multiple linear regression provides the detailed score, allowing the EPP and learner to know that they can still be in danger of failing.

In 2002, the *NCLB Act*, shuffled the deck to reform America's education system. One of the changes of the *NCLB Act* was increased rigor for teacher certification examinations (Darling-Hammond, 2019). Plans and policies were written at the federal level. For example, schools were evaluated based on their Annual Yearly Progress (AYP) and sanctions were issued if AYP goals were not met for three consecutive years (Miller & Hudson, 2007; Lesley, 2016). From 2012 to 2015, the Obama administration revised parts of the *NCLB Act* and in 2015 proposed the *Every Student Succeeds Act* (*ESSA*). *ESSA* (2015) discarded the AYP requirements and returned the accountability back to the state level where requirements became evidenced-based measures to improve standards for all students (Darling-Hammond et al. 2016). For Texas, this translated to the TExES and under the TExES™ EC-6 test Domain IV, each of the competencies outline the standards for which the preservice teacher must demonstrate proficiency to successfully teach EC-6 science (TEA, 2018). Studies have shown that preservice teachers usually score poorly in science Domain IV (Miller & Hudson, 2007; Kazempour & Sadler, 2015).

One of the critical changes that came along with the *ESSA Act* of 2015 was limiting the number of attempts preservice teachers can take certification examination. A second change targeted how the examination was scored and required each of the five subject domains to be passed with a minimum score of 80% rather than using the former composite score which allowed low performance in some subject domains to be offset by higher performance in other domains (Darling-Hammond et al., 2016; Hutson, 2017). The reduction in number of attempts, along with increased pressures to improve performance of students in both mathematics and science placed additional stress on preservice teachers to master all subject domains, and on EPPs to improve performance on certification examinations (Darling-Hammond et al., 2016; Sutcher et al., 2016).

In addition to changes to the structure and scoring of the certification exams, there continues to be a nationwide shortage of teachers (Sutcher et al., 2016). This shortage has been due to an increase in the population of students attending school; an increase in the number of retirees; a decrease in the number of preservice teachers pursuing certification by approximately 33%; a decrease in the passing rate of teachers on their certification exam; and an increase in the standards across all platforms that measures teachers' accountability. The EPPs that prepare preservice teachers can also be sanctioned or receive disciplinary actions if their program fails to produce high quality teachers (Warren, 2017).

Research on determining factors that can affect and predict student performance on examinations continues to be relevant and various statistical methods and academic and environmental factors have been investigated to determine impact (Kazempour & Sadler, 2015; Kim & Corcoran, 2018). For example, Lykourentzou et al., (2009), using a multiple linear regression model, found that the best prediction of performance in an online course was the staging of practice multiple choice examinations early in the course. D'Amico and Dika (2013) examined precollege and other academic factors during early college years that may influence students' success in Science, Technology, Engineering, and Mathematics (STEM) fields and found GPA and success in mathematics were major indicators of success on the examination. Kim and Corcoran (2018) investigated factors that impact preservice teacher academic achievement and showed GPA, along with performance in their EPP, were impactful on a student's test performance. Studies investigating the impact of age and college classification on examination performance revealed that older students, as well as those who are further along in their college classification, showed increased cognitive skills as well as higher GPA (Kim & Corcoran, 2018). Also evident, was that factors investigated, in terms of college classification, focused on the performance of freshmen in college (Graunke & Woosley, 2005). Additionally, similar to freshmen, their study revealed that sophomores were at significant risk of dropping out of college. Furthermore, first-generation students tend to earn lower grades and have a lower completion rate of college compared to the other college counterparts as they are often employed whilst attending college (DeFreitas & Rinn, 2013; Kim & Corcoran, 2018; Martinez et al., 2009; Swecker et al., 2013). In addition, transfer students, compared to non-transfer students, had lower GPAs however, the GPA advantage held by non-transfer students disappeared about a semester after the student transferred (Douglass, 2012; Krieg, 2010). Finally, over the last five decades, increasing numbers of college students engage in part-time work, with approximately 40% of all full-time students having a part-time job (Peters & Draughon, 2017). Since it is anticipated that by 2025 close to 45% of all college students will be attending part-time, the influences on part-time students and what determines their success in college needs to be investigated (NCES, 2017; Peters & Draughon, 2017). With all of these independent variables shown to have some impact on student performance, this study used some of these variables to evaluate their individual, as well as their combined, impact on performance on the science portion of the EC-6 TExES certification examination.

Predicting preservice teachers' performance on their certification examination with the use of predictive models can allow EPPs to identify students who may potentially fail the official state certification examination so they may implement strategies to improve success on a subsequent EC-6 certification exam through remediation, retrieval practice, improved test taking strategies, and other interventions (Masters, 2018). This study used BIOL 1082, a mandatory preservice biology course that covers the biology competencies of the EC-6 TExES examination. Students who volunteered to participate in the study took the practice EC-6 certification examination at the beginning of the semester (pretest) and at the end of the semester (post-test). Additionally, an online Qualtrics™ survey was used to collect self-reported demographics and other pertinent information about the participants. In support of the goal of this study, which was to predict preservice teachers score on the science portion of the EC-6 TExES practice certification exam, the grade in BIOL 1082 as well as 13 additional independent variables from the Qualtrics survey were utilized. The post-test score on the practice exam was used as the dependent variable. Taken together, these variables were used to create multiple linear regression and binomial logistic regression predictive models. These predictive models can arm EPPs with tools to help them identify preservice teachers in need of scaffolding and remediation for content knowledge and will help the preservice teachers maintain and or achieve acceptable levels of academic success. Given this goal, this study set out to answer the following research question:

> Do any of the following explanatory variables: final grade in BIOL 1082 (X1), classification (X2), transfer status (X3), college biology (X4), college chemistry (X5), college physics (X6), college environmental science (X7), college earth science (X8), part-time (X9), credits taking (X10), first-generation college student (X11), relatives with degree in education (X12), and current GPA (X13), individually or in combination predict preservice teachers' performance on the science portion of the practice EC-6 TExES™ examination?

Methods

This study focused on preservice teachers enrolled in the Biology for Educators class (BIOL 1082), a mandatory course for preservice elementary educators, taught at a university in the southwest area of the United States. The participants took a Qualtrics™ survey to identify demographics as well as independent variables associated with performance. The dependent variable was the post-test score on the practice EC-6 TExES certification examination. MLR and BLR were used to develop predictive models associated with student success on the certification examination.

Participants

This study collected data from 170 preservice teachers pursuing a Bachelor of Science in Education with EC-6 teacher certification in the College of Education. These teachers were enrolled in Biology for Elementary Educators (BIOL 1082), within the College of Science, over the span of three consecutive semesters. The course BIOL 1082 can be taken at any time during the program therefore, all four classifications of students: freshman, sophomore, junior and seniors were participants in this study. The only science course for EC-6 TExES certification that had a set time frame for when it can be taken was EDEE, which was only available during the participants senior year. The preservice teachers age ranged from 18 to 35 years old. Most participants (62.4%) were age 18-20. 28.8% were between 21-23 years of age, 6.47% were 24-26, 1.17% were 27-30, and 1.17% were age 31-35. The classification of the preservice teachers was a mixture of all four classification levels with 21.8% freshman, 32.9% sophomore, 37.6% juniors and 7.64% seniors. Approximately 90% of the participants were full-time students. Half of the preservice teachers were transfer students. The participants of this study were predominantly female (97%) which is typically the case seen with the decline of male preservice teachers in early childhood education (Stroud et al., 2006), and is consistent with the general gender distribution for the EC-6 major at this University. The survey was used to identify science coursework completed during high school. The survey showed that 97% took biology, 93.5% took chemistry, 88.2% took physics, 20% took environmental science, and 8.2% took earth science. The participants were also asked if they took biology, chemistry, physics, environmental science, and earth science at college to which they responded: 28.8% took biology, 8.2% took chemistry, 30.6% took physics, 51.2% took environmental science, and 38.8% took earth science. Approximately 65.3% of the participants had a relative who had obtained a degree in education. Only 113 out of 170 (66.5%) of preservice teachers reported their overall GPA of which 5.3% had GPAs of 2.0-2.5, 14.2% had GPAs of 2.51-3.0, 37.3% had GPAs of 3.01-3.5, and 43.4% had GPAs of 3.15-4.0. Approximately 58.1% of preservice teachers reported being first-generation college students. Of the participants, 168 out of 170 (98.8%) preservice teachers completed BIOL 1082 of which 159 out of 170 (93.5%) passed BIOL 1082 with a Grade "C" or better.

Data Collection

Preceding the start of the study, authorization to conduct this research was asked for from the Institutional Review Board (IRB). Preservice teachers who volunteered to participate in the study were required to sign the IRB (Code No. 17-206) consent form before participating. Quantitative and qualitative data was collected from 170 preservice teachers. An online survey (Biology for Educators) was used to collect ex post facto qualitative and quantitative information from preservice teachers which included demographics such as age, classification, previous science courses taken, first generation, part-time or fulltime student status, number of credits already taken, transfer vs non-transfer, and relatives with degrees in education.

A practice test on the science core of the EC-6 TExES™ certification examination was prepared and issued by the TExES™ Advising Office (TAO). The practice EC-6 TExES™ exam was given during the second week of the semester during a class period of BIOL 1082 and labeled pretest. The practice exam is a secured examination developed for the state certification agency and consisted of 45 multiple choice questions asked over the 18 competencies that preservice teachers need to be proficient in over Domain IV of the EC-TExES certification exam. Preservice teachers documented their answers on scantrons, which were evaluated and assessed by the TAO, and their coded responses were returned to the researcher. The coded responses included the 18 competencies and the total number of questions asked over every competency and the number of questions each preservice teacher got correct over that competency and can be seen in Table X. The practice test was given again to the students as a post-test the second to last week of that same semester.

The BIOL 1082 course specifically addressed competencies: C1, C2, C4, C10, C11, C12, C13, and C14 which are the competencies for biology for educators. The preservice teacher degree program does not require a chemistry course and competencies C8 cover topics associated with a chemistry course although they may be taught during a physics course as well (e.g., waves, periodic table). The PHYS 1210 course addressed competencies: C7, C8, and C9 in the subject area of physics. The BIOL 1132 course addressed competencies: C14, and C17 in the subject area of environmental science. The GEOG 1710 course addressed competencies: C15, C16, C17, and C18 in the subject area earth science. The EDEE 4330 course addressed competencies: C3, C5 and C6 and covers the scope and sequence of science education from early childhood to 6th grade. For the practice EC-6 TExES certification exam the number of questions asked over each of the 18 competencies are summarized in Table 1.

Table 1

Number of Questions asked over each Competency of Domain IV EC-6 TExES Certification Examination

Competencies (C) 1-18	Number of questions out of 45 questions asked
C1	3
C2	3
C3	2
C4	2
C5	3
C6	2
C7	3
C8	3
C9	2
C10	2
C11	3
C12	1
C13	2
C14	3
C15	3
C16	3
C17	2
C18	3

Description of Independent Variables and Prediction Models

The regression models used a total of 13 factors, or independent variables, to develop four multiple regression models and four binomial logistic models. For ease of representation, the independent variable will be referred to as follows: grade in BIOL 1082 (X1), classification (X2), transfer (X3), college biology (X4), college chemistry (X5), college physics (X6), college environmental science (X7), college earth science (X8), part-time (X9), credits taking (X10), first-generation (X11), relative with degree in education (X12), and current GPA (X13). The models used the independent variables or factors in the following combinations:

- Full Model: *X1, X2, X3, X4, X5, X6, X7, X8, X9, X10, X11, X12, X13*
- Academics Model: *X1, X10, X13*
- Uncontrolled Factors Model: *X2, X3, X9, X11, X12*
- Forward Regression: all the independent variables were included in the initial stage of building the model.

Statistical Analyses of Study

The analyses that this study employed included two different statistical approaches. The multiple linear regression and the binomial logistic regression are described below.

Multiple linear regression (MLR) is a type of analysis performed to investigate the extent to which independent variables explain the variance of a dependent variable. The analysis yielded a coefficient of determination (R^2) which explains how well the predictor or independent variables explain the variance in the dependent variable (Courville & Thompson, 2001; Schneider et al., 2010). The closer the value of R^2 is to 1 the stronger the ability of the regression model to explain the variance in the dependent variable (Huang and Fang, 2013).

Binomial logistic regression (BLR) is a type of predictive modeling analysis that can be used to assess the association between a dependent variable and two or more independent variables (Kuha & Mills, 2017). The assessment of the fitness of the logistic model occurs at two levels. The first assessment of the Full model is via the chi-square likelihood ratio test where the null model with no predictors is compared with the full model including all predictors. The second assessment is via the Hosmer & Lemeshow (2000) goodness-of-fit test. The entire model fit is assessed by Nagelkerke's R^2, considered a pseudo R square, and is an explanation of the amount of variation in the dependent variable and the ability of the model to correctly classify preservice teachers group membership of the dependent variable (Smith & McKenna, 2013). The null hypothesis of the model is that βs is equal to "0" and the alternative hypothesis is that at least one β is not equal to "0" (Chao-Ying et al., 2002). The difference between the MLR and the BLR models is that with the BLR model, the dependent variable must be dichotomous or binary such as pass or fail.

While logistic BLR model offers a precise cutoff of preservice teachers' ability to pass or fail the science core of the practice EC-6 certification examination, MLR reveals the direct contribution of each of the independent variables and offers the ability to make an approximation of the actual score earned (Kuha & Mills, 2017).

Data Treatment

For multiple linear regression analyses, the dependent variable, which was the post-test score preservice teachers made on the practice exam, was represented as a continuous variable with a range from 1-100. For binomial logistic regression analyses the scores that preservice teachers obtained on their practice exam were converted from the continuous variable score of ≥ 80 as "pass" which was coded to "1", and $< 80\%$ as "fail" and coded to "0" for the dichotomous result. Some of the data from the survey were converted from "yes" and "no" into dichotomous values "1" and "0" all which are summarized in Table 2.

Each of the independent variables were individually used in a simple linear regression analysis with the dependent variable (the practice exam score), so that one could use a single variable which was statistically significant at $p \leq 0.05$ to predict the performance of preservice teachers who may not have data for all 13 independent variables.

Table 2

Summary of Variable Coding used in the Study

Variables	Description	Variables	Description
X1	Categorical: Pass "1" and Fail "0"	X7	Dichotomous
X2	Categorical		0=Did not take college environmental science
	1=Freshman		1= Took college environmental science
	2=Sophomore	X8	Dichotomous
	3=Junior		0=Did not take college earth science
	4=Senior		1= Took college earth science
X3	Dichotomous	X9	Dichotomous
	0= Did not transfer		0= not part time
	1= Transferred		1=Part-time
X4	Dichotomous	X10	Continuous variable ranges from "0" to "24" or above
	0=Did not take college biology	X11	Dichotomous
	1= Took college biology		0= Not first-generation college student
X5	Dichotomous		1=First-generation college student
	0= Did not take college chemistry	X12	Dichotomous
	1=Took college chemistry		0=No relative with degree in education
X6	Dichotomous		1=relative with degree in education
	0=Did not take college physics	X13	Continuous variable ranges from 2.0 to 4.0
	1=took college physics		

Data Analysis

Both descriptive and inferential statistics were used to assess the data in terms of the numbers and percentages of preservice teachers who: passed the pretest, failed the pretest, passed both the pretest and post-test, and the differences in percentage between the pretest and the post-test. To answer the research question using multiple linear regression analyses, the effects of all 13 independent variables (X1-X13) on the ability of preservice teachers to pass the practice EC-6 TExES certification exam (dependent variable) were analyzed. This was repeated for a three-predictors model (Academics (X1, X10, and X13), a five predictors model (Uncontrolled Factors (X2, X3, X9, X11, X12) and a forward linear regression model.

To answer the research question using the binomial regression analyses, a 13-predictors logistic regression model (Full) was fitted to the data to examine the study's hypothesis of the likelihood that a preservice teacher will pass the practice EC-6 TExES certification exam based on the predictors. This was repeated for a three-predictors model (Academics), a five predictors model (Uncontrolled Factors) and a forward logistic regression model. The data was screened to verify that assumptions have been met.

Results

The impact of the BIOL 1082 course and its effect on the improvement in proficiency on each of the EC-6 TExES Domain IV 18 competencies was conducted by calculating the difference between performance of preservice teachers on pretest and post-test of the practice exam. The 18 competencies were categorized based on what was or will be covered in each of the prerequisite science courses that preservice teachers needed to take prior to taking the official EC-6 TExES examination. Though some of the Domain IV EC-6 TExES competencies were not designated to be covered in the BIOL 1082 course, the gains of all 18 competencies were calculated for the competencies covered in physics, environmental science, earth science, and scientific methods. The distribution and performance on each of the competencies is shown in Table 3. The pre/post-test included 45 questions (Table 1). As shown in Table 3, the increase in performance average (points) for biology was 5.82 points. In descending order, the performance average increase for environmental science was 5.70 points (5 questions); followed by Earth science (2.75; 11 questions), physics (2.64; 8 questions), chemistry (1.28; 5 questions) and science methods (1.5; 17 questions) (See Table 1 for # of questions/competency).

Table 3

Gains in Competencies 1-18 of Domain IV of EC-6 TExES Practice Exam

Competencies Domain IV Science EC-6 TExES	Course at university	Subject matter covered	Pretest average	Posttest average	Change in points
C1, C2, C4, C10, C11, C12, C13, C14	BIOL 1082	Biology	71.29	77.11	+5.82
C8, C9		Chemistry	75.58	76.86	+1.28
C7, C8, C9	PHYS 1210	Physics	66.16	68.80	+2.64
C14, C17	BIOL 1132	Environmental Science	74.88	80.58	+5.70
C15, C16, C17, C18	GEOG 1710	Earth Science	63.68	66.43	+2.75
C3, C5, C6	EDEE 4330	Science Methods	86.46	88.04	+1.58

Descriptive Statistics

Generally, the study showed an improvement in performance on the post-test in comparison to the pretest (Table 4). Independent variables BIOL 1082 (X1), transfer (X3), part-time (X9), first-generation (X11), and relative with degree in education (X12) each had 42 out of 170 preservice teachers who passed the pretest, and 67 out of 170 who passed the post-test. The variable that explained the most variance in the model to predict performance on the practice EC-6 TExES exam was X1 (grade in BIOL 1082). Preservice teachers who failed BIOL 1082 experienced no success on either the pretest or post-test of the practice EC-6 TExES exam.

The overall post-test passing rate was approximately 40%. Freshmen, sophomore, and junior preservice teachers had pass rates between 23% and 34%. Seniors, on the other hand, experienced zero success on the pretest and about 15% success on the post-test. Preservice teachers who were non-transfer students had a 12% higher passing rate in the pretest and 16% higher on the post-test compared to transfer students. Full-time preservice teachers outperformed those who were part-time, students who were not first-generation college students outperformed first generation college students, and preservice teachers who had family members with degrees in education outperformed those who did not.

Compared to preservice teachers taking 15 or fewer credits, preservice teachers taking 16-22 credits had less success in the pretest but then were within the range of performance percentage between 40-49% on the post-test. 55.1% of preservice teachers who had a GPA between 3.51-4.0 passed the post-test. Surprisingly, those with GPAs between 2.0-2.5 followed this with a pass rate of 50%.

Table 4

Descriptive Statistics of Variables

Variables	Categories	# of participants	Passed pretest	%	Passed posttest	%	Passed both	%	Difference Pre/post (%)
Grade in BIOL 1082 (X1)	Passed BIOL 1082	159	42	26.40	67	42.10	36	22.60	15.70
	Failed BIOL 1082	9	0	0	0	0	0	0	0
	Total	168	42	25	67	40	36	21.40	14.70
Classification (X2)	Freshman	37	9	24.30	15	40.50	9	24.30	16.20
	Sophomore	56	18	33.90	25	44.60	14	25	10.70
	Junior	64	15	23.40	25	39.10	13	20.30	15.70
	Senior	13	0	0	2	15.40	0	0	15.40
	Total	170	42	25.30	67	39.40	36	21.20	14.10
Transfer (X3)	Transfer	86	16	18.60	27	31.40	13	15.10	12.80
	Non-transfer	84	26	30.90	40	47.60	23	27.40	16.70
	Total	170	42	24.70	67	39.40	36	21.20	14.70
College Science Courses (X4-X8)	Biology	49	10	20.40	13	26.50	6	12.20	6.10
	Chemistry	14	3	21.40	2	14.30	1	7.10	-7.10
	Physics	52	10	19.20	17	32.70	7	13.50	13.50
	Environmental Science	87	16	18.40	33	37.90	14	16.10	19.50
	Earth Science	66	16	24.20	29	43.90	15	22.70	19.70
Part-time (X9)	Part-time	16	2	12.50	4	25	1	6.25	12.50
	Full-time	154	40	25.90	63	40.90	35	22.70	15
	Total	170	42	24.70	67	39.40	36	21.20	14.70
Credits Taking (X10)	3 to 7	6	0	0	1	16.70	0	0	16.70
	8 to 12	35	11	31.40	17	48.60	8	22.90	17.20
	13 to 15	76	22	28.94	34	44.70	20	26.30	15.80
	16 to 22	25	4	16	10	40	4	16	24
	Total	142	37	26	62	43.70	32	22.50	17.70
First-generation (X11)	Yes	70	12	17.10	21	30	10	14.30	12.90
	No	100	30	30	46	46	26	26	16
	Total	170	42	24.70	67	39.40	36	21.20	14.70

Table 4 (*Continued*)

Variables	Categories	Number of students	Passed pretest	%	Passed posttest	%	Passed both	%	Difference Pre/post (%)
Relative with degree in Education (X12)	Relative	59	18	30.50	30	50.80	16	27.10	20.30
	No relative	111	24	21.60	37	33.30	20	18	11.70
	Total	170	42	24.70	67	39.40	36	21.20	14.70
Current GPA (X13)	2.0-2.5	6	3	50	3	50	3	50	0
	2.51-3.0	16	1	6.25	7	43.70	0	0	37.50
	3.01-3.5	42	8	19	9	21.4	5	11.90	2.40
	3.51-4.0	49	18	36.70	27	55.10	17	34.70	18.40
	Total	113	30	26.50	46	40.70	25	22.10	14.20

Multiple Linear Regression Univariate Analyses

Studies have suggested that in a multiple linear regression there should be at least 10 observations per independent variable (Sperandei, 2014). Shown in Table 5 are independent variables X1-X13 used in univariate or simple linear regression analyses with the dependent variable. As shown in Table 5, X1, X2, X3, X4, X10, and X13 were statistically significant at $p < 0.05$. The coefficient of determination (R^2), which is the proportion of variance in the practice test score that was explained by the independent variable, are explained in terms of: BIOL 1082 (X1), which explains 16.3% of the variance in the practice exam score, followed by current GPA (X13), then number of credits taking (X10), and transfer status (X3), which each individually explained approximately 5% of the variance in the dependent variable. College biology (X4) follows at approximately 3.1% and then classification (X2) at 2.4%. Independent variables college chemistry (X5), college physics (X6), college environmental. Science (X7), college earth science (X8), part-time (X9), first-generation (X11), and relative with degree in education (X12) each explains <2% of the variance in the dependent variable. Though most studies suggest pursuing variables with a p-value of 0.05 or less, Hosmer and Lemeshow (2000) recommend that a p-value of 0.25 or less can be pursued to avoid the loss of variables that may be valuable to the research, or variables that when combined with another variable may present compelling evidence of effect on dependent variable. Variables X5, X6, X7, and X12, which had levels of significance above 0.25, were kept in the Full model since previous studies have suggested that prior knowledge in subject areas as well as having a relative with similar experience may influence performance on student achievement and thus on the practice EC-6 TExES examination (Kim & Corcoran, 2018).

Table 5

Output of each of the Independent Variables Individually Regressed with the Dependent Variable Performance on Practice Exam

Variable	R	R^2	Adjusted R squared	Sig.	B_1	Standard Coefficient Beta
X1	0.404	0.163	0.158	0*	0.471	0.404
X2	0.154	0.024	0.018	0.045*	-1.71	-0.154
X3	0.219	0.050	0.042	0.004*	-4.352	-0.219
X4	0.176	0.031	0.026	0.022*	-3.860	-0.176
X5	0.093	0.009	0.003	0.228	-3.361	-0.093
X6	0.080	0.006	0.001	0.302	-1.716	-0.080
X7	0.072	0.005	-0.001	0.354	-1.383	-0.072
X8	0.130	0.017	0.011	0.091	2.647	0.130
X9	0.120	0.014	0.008	0.120	-4.075	-0.120
X10	0.224	0.050	0.043	0.007*	0.741	0.224
X11	0.107	0.011	0.006	0.165	-2.159	-0.107
X12	0.083	0.007	0.001	0.286	1.718	0.083
X13	0.236	0.056	0.047	0.012*	4.630	0.236

*Indicates statistically significant at $p \leq 0.05$

Table 6

Model Summary of the Multiple Linear Regression Prediction Models

Name of Multiple Linear Regression Models (MLR)	R^2	p	β_0	$\beta_x X1$	$\beta_x X2$	$\beta_x X3$	$\beta_x X4$	$\beta_x X5$	$\beta_x X6$	$\beta x X7$	$\beta x X8$	$\beta x X9$	$\beta x X10$	$\beta x X11$	$\beta x X12$	$\beta x X13$
Full MLR	0.323	0.000*	24.426	0.548	-1.743	-0.795	-1.530	-4.683	0.224	2.726	1.637	3.626	0.807	-0.990	2.609	-1.013
Academics MLR	0.286	0.000*	17.877	0.486									0.726			2.013
Uncontrolled MLR	0.039	0.042*	78.629		-0.258	-4.025						-1.916				
Forward MLR 1	0.274	0.000*	21.504	0.647												
Forward MLR 2	0.313	0.000*	18.332	0.562									0.747			

*Indicates statistically significant at $p \leq 0.05$

Multiple Linear Regression Model Summary

A multiple linear regression model was fitted to the data to evaluate the relationship between preservice teachers score on the practice exam and all 13 of the independent variables in the Full model summarized in Table 6. The model was statistically significant (F (13,93) = 4.451, p< 0.05) with an adjusted R^2 value of 0.323 interpreted as 32.3% of the variance in the practice exam score can be explained by the model.

The model summary for the Academics model included the variables BIOL 1082 (X1), number of credits taking (X10), and current GPA (X13). The model was found to be statistically significant (F (3, 94) = 13.977, p< 0.05), with an adjusted R^2 of 0.286 which is interpreted as 28.6% of the variance in practice exam score can be explained by the Academics Model as shown in Table 6.

The Uncontrolled Factors model included the variables classification (X2), transfer status (X3), part time (X9), first generation (X11), and relative with a degree in education (X12). The model was found to be statistically significant F (5, 161) = 2.365, p< 0.05), with an R^2 of 0.039, which is translated as 3.9% of the variance in the practice exam is explained by the Uncontrolled Factors Model as shown in Table 6.

In Forward linear regression Model 1 was statistically significant (F (1, 93) = 36.421, p< 0.05 with an R^2 value of 0.274 which explains that 27.4% of the variance in practice exam score can be explained by be explained by BIOL 1082 (X1). In Model 2, (F (1, 92) = 6.283, p< 0.05 with an R^2 value of 0.313 which explains that 31.3% of the variance in practice exam score can be explained by be explained by BIOL 1082 (X1) and number of credits taking (X10) as shown in Table 6.

Multiple Linear Regression Coefficients Summary

Coefficients that describe the relationship between the independent variable and the dependent variable provide information about the amount of increase or decrease in a practice exam score that can be predicted by a single unit increase in the independent variable. The coefficients of each of the four multiple regression models are summarized in Table 6.

In the Full MLR model (Table 6), the independent variable, BIOL 1082(X1), was shown to be statistically significant at p<0.05. The coefficient for X1 is 0.548 which is interpreted as for every unit increase in a student's Biology grade in the BIOL 1082 course, a 0.548-unit increase is predicted in the practice exam score, holding constant all the other independent variables. In this model, a preservice teacher is anticipated to have an increased chance of passing the practice examination if they passed BIOL 1082; a decreased chance of passing based on their seniority in classification (X2) as they progress from freshman to senior; a decreased chance of passing the practice exam if they are a transfer student (X3); a decreased chance of passing the practice exam if they took a college biology or chemistry course (X4 and X5); an increased chance of passing if they have taken college physics, environmental science, or earth science (X6, X7, and X8); an increased chance of passing for preservice teachers who identified as part-time (X9) and if they are have a relative with a degree in education (X12); an increased chance of passing the practice certification exam as the number of credits they are taking, (X10) increase in quantity; and a decreased chance of passing if they are first-generation college students (X11), and for every unit increase in current GPA (X13).

In the Academics MLR model (Table 6), both BIOL 1082 (X1), and number of credits taking (X10) were statistically significant at p<0.05. In this model, the coefficient for BIOL 1082 (X1), 0.486 is interpreted as for every unit increase in BIOL 1082 (X1), the predicted score on the practice exam is expected to increase by 0.486 points. For both number of credits taking (X10) and current GPA (X13) for every unit increase in these two variables, the predicted score on the practice exam is predicted to increase by 0.726 points and by 2.013 points respectively.

In the Uncontrolled Factors MLR model (Table 6), independent variable transfer status (X3) was statistically significant at $p<0.05$. For independent variables classification (X2), part-time (X9), and first-generation (X11), a decrease is predicted in the practice exam score for these variables. For transfer status (X3) , the practice exam score is predicted to be 4.0253 points lower for preservice teachers who transferred compared to those who are not transfer students. For relative with degree in education (X12) the practice exam score is predicted to be 1.345 points higher for preservice teachers who have a relative with a degree in education compared to those who did not.

Finally, for the forward MLR model (Table 6), independent variable BIOL 1082 (X1) was placed into the model first and it was statistically significant at $p<0.05$. The second independent variable that was pulled into the forward regression model was number of credits taking (X10). Both were statistically significant and an increase in the practice exam score was predicted for these two variables.

The Full multiple linear regression model, the Academics multiple linear regression model and the Forward linear regression model yielded values of R^2 which explained between 28%-32 % of the variance in the dependent variable. The variables BIOL 1082 (X1), transfer (X3), number of credits taking (X10) and current GPA (X13) were the only variables that maintained statistical significance at $p<0.05$ in one or more of the multiple linear regression models. The Uncontrolled Factors multiple linear regression model did not yield a model that can explain a high enough variance in the dependent variable at just 3.9%. However, the null hypothesis was rejected in knowledge that some of the independent variables do show evidence of impacting preservice teachers score on the practice EC-6 examination.

Binomial Logistic Regression Univariate Analyses Summary

In Table 7, the dependent variable was independently regressed upon each of the independent variable in a univariate logistic regression analysis of which Bio Grade (X1), Transfer (X3), Bio Course (X4), Chem Course (X5), First-generation (X11), Relative with degree in Education (X12), and Current GPA (X13) were statistically significant at $p \leq 0.05$ Hosmer and Lemeshow (2000) recommended that independent variables that are not statistically significant may be kept in a prediction model due to the impact they may have on the dependent variable and may experience increased significance or decreased significance when in conjunction with other independent variables. While some of the other variables did not qualify for Hosmer and Lemeshow's (2000) argument of keeping variables whose *p*-value was ≤ 0.25, the independent variables college environmental science (X7), college earth science (X8), and number of credits aking (X10) were kept due to supporting evidence from other studies that these variables do influence student performance on examinations (Kim & Corcoran, 2018).

Binomial Logistic Regression Variables in the Equation

The column for Y intercept "B" is the coefficient of the equation and describes the relationship between the independent variable and the dependent variable which informs about the amount of increase or decrease in log odds for passing the practice exam that can be predicted by a single unit increase in the independent variable. The results are summarized for the four different logistic models and presented in Table 8.

In the Full Logistic Model, shown in Table 8, χ^2 of 33.265 (13, N= 97, $p < .05$) only the independent variables grade in BIOL 1082 (X1) and Relative with degree in Education (X12) were shown to be statistically significant at $p < 0.05$. In this model, the log of the odds that a preservice teacher passes the practice EC-6 TExES certification exam was positively related to their grade in BIOL 1082. The coefficient is 0.096 and the ODDS ratio is 1.101 which is interpreted as for every unit increase in BIOL 1082 (X1), the logit or the odds of passing the practice exam increases by 0.096-unit and that exponentially for ODDS ratio translates to the odds of passing the practice exam increasing by 1.101

(Table 7). Classification (X2), transfer status (X3), college biology or college chemistry (X4 and X5), part-time status (X9), first-generation status (X11), and current GPA (X13), each with an ODDS ratio <1, are associated with decreased odds of passing the practice EC-6 TExES certification exam for every unit increase in that variable. The variables College physics (X6), college environmental science (X7), or college earth science (X8), , and Relative with degree in Education (X12) each with a positive β and an ODDS ratio >1, are associated with increased odds of passing the practice EC-6 TExES certification exam for every unit increase in that variable.

Table 7

Independent Variable Individually Regressed with the Dependent Variable in Binomial Logistic Regression

Independent Variable	Chi-square *df* (1)	*p-value*
X1 (exam score)	12.418	0*
X2 (classification)	1.46	0.227
X3 (transfer status)	4.707	0.03*
X4 (college biology course)	4.95	0.026*
X5 (college chemistry course)	4.597	0.032*
X6 (college physics course)	1.437	0.231
X7 (environmental science course)	0.164	0.686
X8 (Earth science course)	0.923	0.337
X9 (employed part-time	1.624	0.203
X10 (# of credits taken)	0.593	0.441
X11 (1st generation student)	4.479	0.034*
X12 (relative in education)	4.717	0.03*
X13 (GPA)	4.297	0.038*

Note. *Indicates statistically significant at $p \leq 0.05$

Per the Academics Logistic Regression Model, as shown in Table 8, χ^2 of 12.834 (3, N= 97, $p<.05$) only grade in BIOL 1082 (X1) is statistically significant at $p<0.05$. For X1, the coefficient is 0.067 and the ODDS ratio is 1.069, which is interpreted as for every unit increase in X1, the logit or the odds of passing the practice exam increases by 0.067-unit and that exponentially for ODDS ratio translate the odds of passing the practice exam increased by 1.069. For independent variables credits taking (X10) and current GPA (X13) though not statistically significant in the model, both are associated with an increase in the odds of passing the practice EC-6 TExES certification exam.

For the Uncontrolled Factors Logistic Model, as shown in Table 8, χ^2 of 13.119 (5, N= 169, $p<.05$) transfer status (X3) was statistically significant at p<0.05. Independent variables classification (X2), transfer (X3), part-time (X9), and first-generation (X11) are each associated with a decrease in the ODDS chance of passing the practice exam with an odds ratio <1. For the independent variable relative with degree in education (X12), the odds of passing the practice exam increases by 0.597 unit and exponentially for the ODDS ratio the odds of passing the practice exam is 1.816 times more likely for a preservice teacher who has a relative with a degree in education compared to those who do not.

In the forward logistic regression model, as shown in Table 8, grade in BIOL 1082 (X1) was pulled into the model first yielding the results summary χ^2 of 11.042 (1, N= 97, $p<.05$) with the odds of passing the practice exam increasing by 0.093-unit and exponentially for ODDS ratio this translates to the odds of passing the practice exam increasing by 1.098. In step 2 of the model, relative with a degree in education (X12) was pulled in addition to BIOL 1082 X1. Both X1 and X12 were statistically significant and their positive β coefficient and odds ratio values <1 were associated with an increased likelihood and ODDs of preservice teachers passing the science portion of the practice EC-6 TExES certification examination which can be seen in Table 8.

Table 8

Coefficient of Variables in the Equation and Goodness of Fit for Logistic Models

Binomial Logistic Regression Model	Predictors	β	*SE* β	Wald's χ^2	*df*	*p*	e^{β} (odds ratio)	95% C.I.for EXP(B) Lower	Upper
Full Logistic Regression Model	Constant	-9.674	3.998	5.856	1	0.016*	NA		
	X1 exam score	0.096	0.039	5.983	1	0.014	1.101	1.019	1.19
	X2 classification	-0.263	0.369	0.506	1	0.477	0.769	0.373	1.585
	X3 transfer status	-0.271	0.727	0.138	1	0.71	0.763	0.183	3.174
	X4 college bio course	-0.687	0.75	0.841	1	0.359	0.503	0.116	2.185
	X5 college chem course	-21.112	14907	0	1	0.999	0	0	0
	X6 college phyics course	0.565	0.623	0.822	1	0.365	1.759	0.519	5.962
	X7 college env sci course	0.558	0.584	0.914	1	0.339	1.748	0.556	5.493
	X8 college Earth sci	0.207	0.553	0.14	1	0.708	1.23	0.416	3.633
	X9 work part-time	-0.047	1.176	0.002	1	0.968	0.954	0.095	9.56
	X10 # credits	0.099	0.12	0.679	1	0.41	1.104	0.873	1.397
	X11 1st generation	-0.224	0.549	0.166	1	0.684	0.8	0.272	2.347
	X12 relative in edu	1.56	0.6	6.75	1	0.009*	4.759	1.467	15.438
	X13 GPA	-0.071	0.578	0.015	1	0.902	0.932	0.3	2.893
	Overall model evaluation			χ^2	*df*	*p*			
	Goodness-of-fit test Hosmer & Lemeshow			10.06	8	0.261			
Academic Logistic Regression Model	Constant	-9.264	2.872	10.407	1	0.001	0		
	X1 exam score	0.067	0.033	4.222	1	0.04*	1.069	1.003	1.14
	X10 # credits	0.092	0.082	1.261	1	0.262	1.097	0.934	1.288
	X13 GPA	0.544	0.478	1.295	1	0.255	1.724	0.675	4.403
	Overall model evaluation			χ2	*df*	*p*			
	Goodness-of-fit test Hosmer & Lemeshow			21.53	8	0.006			
Uncontrolled Factors Logistic Regression Model	Constant	-0.223	0.494	0.204	1	0.651			
	X2 classification	0.119	0.234	0.259	1	0.611	1.127	0.712	1.784
	X3 transfer status	-0.88	0.43	4.188	1	0.041*	0.415	0.178	0.963
	X9 work part-time	-0.346	0.643	0.289	1	0.591	0.708	0.201	2.496
	X11 1st generation	-0.591	0.37	2.553	1	0.11	0.554	0.268	1.143
	X12 relative in edu	0.597	0.362	2.711	1	0.1	1.816	0.893	3.694
	Overall model evaluation			χ2	*df*	*p*			
	Goodness-of-fit test Hosmer & Lemeshow			10.79	8	0.214			

Table 8(*Continued*)

	Binomial Logistic Regression Model	Predictors	β	*SE* β	Wald's χ^2	d_f	p	e^{β}(odds ratio)	95% C.I.for EXP(B) Lower	Upper
Step 1		X1 exam score	0.093	0.031	9.009	1	0.003*	1.098	1.073	1.269
		Constant	-8.274	2.681	9.525	1	0.002	0		
Step 2		X1 exam score	0.098	0.031	9.88	1	0.002*	1.103	1.078	1.275
		X12 relative in edu	1.343	0.488	7.587	1	0.006*	3.83	1.324	13.448
		Constant	-9.167	2.728	11.29	1	0.001	0		
Step 3		X1 exam score	0.11	0.033	11	1	0.001*	1.116	1.093	1.318
	Forward Logistic Regression Model	X5 college chem course	-21.589	14533	0	1	0.999	0	0.000	
		X12 relative in edu	1.555	0.526	8.721	1	0.003*	4.733	1.688	23.759
		Constant	-10.094	2.896	12.15	1	0	0		
		Overall model evaluation			$\chi 2$	d_f	p			
Step 1		Goodness-of-fit test Hosmer & Lemeshow			6.654	8	0.574			
Step 2		Goodness-of-fit test Hosmer & Lemeshow			6.578	8	0.583			
Step 3		Goodness-of-fit test Hosmer & Lemeshow			4.39	8	0.82			

*Indicates statistically significant at $p \leq 0.05$.

Binomial Logistic Regression Prediction Accuracy

In Table 9, the classification table of the model with all 13 variables (Full Logistic Model) has an overall prediction accuracy of 75.26%. In the "failed" practice test row, a total of 56 (45 +11) were observed as failures. However, the model correctly predicted 45 out of the 56 (80.4%) of those to be failures and incorrectly predicted 11 out of 56 (19.6%) as passes. In the "passed" practice test row out of the 41 observed to have passed, the model incorrectly predicted 13 out of 41 (31.7%) as failures and 28 out of 41 (68.3%) as passes.

The Academics Logistic Model in Table 9 had an overall prediction accuracy of 66.3%. In the "failed" practice test row, a total of 57 (45 +12) were observed as failures. However, the model correctly predicted 45 out of the 57 (78.9%) of those to be failures and incorrectly predicted 12 out of 56 (21.1%) as passes. In the "passed" practice test row out of the 41 observed to have passed, the model incorrectly predicted 21 out of 41 (51.2%) as failures and 20 out of 41 (48.8%) as passes.

The prediction accuracy for the Uncontrolled Factors Logistic Model in Table 9 was 62.3% for correctly predicting 83.3% of preservice teachers who failed the practice test and 30.8% accuracy for correctly predicting preservice teachers who passed the practice test.

Forward logistic regression prediction accuracy in Table 9: Model 1 had a prediction accuracy of 65.9%, Model 2 had an overall prediction accuracy of 70.1% and the overall prediction accuracy for Model 3 was 72%. Model 1, 2, and 3 all had a prediction accuracy for preservice teachers who failed the practice at 79%. The prediction accuracy for preservice teachers who passed the practice test for all three forward logistic models were: Model 1 (49%), Model 2 (59%), and Model 3 (63%). The probability of correctly predicting the correct group membership increases (sensitivity) as the probability of predicting the incorrect group membership decreases (specificity).

Table 9

Classification Table of the Prediction Accuracy for Logistic Regression Models

	Logistic Regression Model	Observed	Predicted		% Correct
			Failed practice test	Passed practice tes	
	Full	Failed practice test	45	11	(45/56) 80.40%
		Passed practice test	13	28	(28/41) 68.30%
		Overall % correct			(73/97) 75.26%
	Academics	Failed practice test	45	12	(45/57) 78.9%
		Passed practice test	21	20	(20/41) 48.8%
		Overall % correct			(65/98) 66.3%
	Uncontrolled Factors	Failed practice test	85	17	(85/102) 83.3%
		Passed practice test	47	21	(21/68) 30.8%
		Overall % correct			(106/170) 62.3%
Step 1	Forward Logistic Regression Model	Failed practice test	44	12	(44/56) 78.6%
		Passed practice test	21	20	(20/41) 48.7%
		Overall Percentage			(64/97) 65.9%
Step 2		Failed practice test	44	12	(44/56) 78.5%
		Passed practice test	17	24	(24/41) 58.5%
		Overall Percentage			(68/97) 70.1%
Step 3		Failed practice test	44	12	(44/56) 78.5%
		Passed practice test	15	26	(26/41) 63.4%
		Overall Percentage			(70/97) 72.2%

Discussion

In some longitudinal and standalone studies conducted to gauge students' success, there is supporting evidence suggesting that academic readiness and success on examinations can be predicted by GPA, full-time status, high self-efficacy, coaching, and other environmental factors (Frizzell, 2014; Gard, 2011; Kazempour & Sadler, 2015; Kim & Corcoran, 2018). While most of these studies focused on factors that may impact the probability of passing a course and others focused on passing a standardized test, most of these studies clumped different subject matters together, neglecting the fact that there are some factors that affect performance that may be unique to specific subject matters (Bains, 2011; Warren 2017).

The *Every Student Succeeds Act* (ESSA) brought changes to the scoring and number attempts that preservice teacher have when taking their state certification examination as well as it increased the standards for Educator Preparation Programs (EPPs) (Every Student Succeeds Act, 2015). EPPs while tasked with preparing preservice teachers for their state certification examination, are also faced with maintaining their accreditation status at 85% pass rate in one academic year (Rickenbrode et al. 2018; Warren, 2017). In Texas, preparation for the Texas Examinations of Educator Standards (TExES) certification examination by (Early Childhood to Six) EC-6 preservice teachers include limited attempts at passing their state certification examination at only five attempts as well as more stringent scoring whereby they are now faced with earning an 80% on each of the five subject matter which means proficiency of each subject matter is mandatory (TEA, 2016). Prior to ESSA 2015, EC-6 TExES preservice teachers were able to mask their inadequacies of a specific subject matter because the scores of each of the five core subjects were combined into one score and if that score was at or above 80%, it was considered a pass (TExES™ program preparation manual, 2018; Warren, 2017). It is now crucial that EC-6 TExES preservice teachers obtain mastery in each of the five subject matters of: English Language Arts Reading, the Science of Teaching Reading, Mathematics, Social Studies, Science, and Fine Arts, Health, and Physical Education (TExES™ program preparation manual, 2018).

Bains (2011) investigated preservice teachers' pass rate of individual subject matters of EC-6 Generalist examination, but the study did not examine factors that can impact actual scores. Gard (2011) examined the prediction of performance on the individual subject areas, such as preservice teachers' performance on TExES 8-12 history, which is a standalone certification subject matter and does not have other variables which may impact performance based on different subject matters. Fang and Wang (2013) investigated the best statistical tools to predict performance at the best performance accuracy, but the focus was on how well an engineering course performance can be predicted using different models. Warren (2017) investigated predictive factors that can influence teacher candidates in EPPs, but this study focused on competing factors that can impact preservice teachers before they even start the EPP program. Another study focused on comparing performance on the content examination vs the pedagogy part for early childhood preservice teachers (Capraro et al., 2005). Other studies focused on preservice teachers' perceptions and self-efficacy (Kim & Corcoran, 2018). Another study (Corcoran and O' Flaherty, 2018) focused on factors that can predict preservice teachers' effectiveness in classroom teaching and thus was not focused on factors impacting the actual exam. These studies either explored performance on the entire certification examination, or on other pre-requisite factors, and thus far, no single study has narrowed down their investigation into the performance on distinct subject matters within a single certification examination. Creating predictive model(s) based on potential independent variables or factors that can predict EC-6 TExES preservice teachers' performance on the individual subject matter of science within the content portion of the certification examination was the focus of this study and serves to fill the gap in the literature which can inform EPPs teachers and preservice teachers alike in every early childhood to six grade certification programs everywhere.

Several studies investigating factors that can influence preservice teachers' success on certification examinations highlighted factors such as age, gender, ethnicity, workload, GPA, familial influence, and performance in their tertiary education program that were significant influencers on their performance on the overall examination (Bain, 2011; Gard, 2011; Huang & Fang, 2013; Warren, 2017). However, most of these studies were focused on holistic examination performance where more than one subject area was combined. Based on different attitudes, perceptions, confidence of proficiency that preservice teachers have on different subject matters this study explored some of the prior factors as well common ex post facto factors that preservice teachers listed which may impact their performance on the science portion of the EC-6 TExES certification examination.

A mixture of descriptive statistics, multiple linear regression, and binomial logistic regression were used in this study to investigate the impacts, if any, that the independent variables had on the practice exam success (Huang & Fang, 2013; Warren, 2017). Researchers preferring multiple linear regression have argued that while binomial logistic regression may successfully predict an individual's ability to pass or fail, a pass may be within boundary of a failure and that person may still be in jeopardy of failing the examination (Huang & Fang, 2013). The employment of both multiple linear regression and binomial logistic regression result in the added benefit that while a binary logistic regression predictive model can help predict a preservice teacher's likelihood of passing or failing the examination due to discrete values associated with either a "pass" or "fail", a multiple linear regression prediction model can offer a more precise score for preservice teachers on a scale from 0 to 100 (Huang & Fang 2013; Khajuria, 2007).

Using MLR to build predictive models has been a strategy used to gauge success in many academic settings. Use of the coefficient of determination (R^2) along with statistical significance have been used as rapid analytic tools for exploring whether predictive variable(s) have impact on the performance outcome of learners (Karamazova et al., 2017; Yang et al., 2018). Each of the MLR models was statistically significant at $p \leq 0.05$ as shown in Table 10. The Full model explained 32.3% of the variance in the practice exam score. The Academics model explained 28.6% of the variance in the practice exam score. The Uncontrolled Factors model explained only 3.9% of the variance in the practice exam score. The forward regression model explained 31.3% of the variance in the practice exam score. The predictor variable which was most often found in all models to be statistically significant was Grade in Biol 1082 (X1).

Table 10

Multiple Linear Regression Models Comparison

Model	R^2	Adjusted R^2	p-value
Full Model (All 13 variables)	0.417	0.323	0.000*
Academic Model	0.308	0.286	0.000*
Uncontrolled Factors Model	0.068	0.039	0.042*
Forward Regression Model	0.327	0.313	0.014*

*Indicates statistically significant at $p \leq 0.05$.

The prediction accuracy of each of the binomial logistic model is summarized in Table 11. Remarkably, the models provided better prediction for the likelihood of failure rather than the likelihood for success on the practice exam. Given that the pass rate on the pretest was 42 out of 170 (24.7%) and the pass rate on the post-test was 67 out of 170 (39.4%), then there may be an advantage of the model predicting failure so that the preservice teachers predicted to fail can be identified and recommended for remediation prior to their official EC-6 TExES examination (Shipe et al., 2019). Each model was able to predict preservice teachers at risk of failing with an accuracy of at least 79%. The full model was the best at predicting who was likely to fail at 80.40%, pass at 68.3% and overall, at 75.30%. The Uncontrolled factors model was the most accurate at predicting failure at 83.3% and simultaneously the least accurate at predicting success at 30.8%. The forward logistic model correctly identified 79% of the preservice teachers expected to fail and 59% expected to pass. The overall prediction accuracy of the models also suggests that the Full logistic model provided the best overall predictor model (75.30%). All four logistic regression model were statistically significant at $p \leq 0.05$ which rejects the null hypothesis that states that the independent variables will not have any effect on preservice teachers' performance (Huang & Fang 2013).

Table 11

Binomial Logistic Regression Models Comparison

Prediction Model	Correctly identified for failing practice test (At-risk))	Correctly identified for passing practice test	Overall % Correct
Full Model (all 13 variables)	80.4% (45 out of 56)	68.3% (28 out of 41)	75.30
Academics Logistic Model	78.9% (45 out of 57)	48.8% (20 out of 41)	66.30
Uncontrolled Factors Logistic Model	83.3% (85 out of 102)	30.8% (21 out of 68)	62.30
Forward Regression Logistic Model	79% (44 out of 56)	59% (24 out of 41)	70

Based on the findings of the study, the full predictive models for the MLR model explained the largest variance in the dependent variable at 32.3% and for the BLR model correctly predicted an overall 75.26% of preservice teachers' successes and failures on the practice exam. However, the full model consists of 13 independent variables, and it may not always be possible to collect more than ten data points for each preservice teacher to successfully use the full model. For this reason, other models may better serve the purpose to predict success on the certification examination. In this study, the simplest model that was most significant in predicting performance on the practice exam was the grade in BIOL 1082 (X1). This model may easily be used for an EPP to evaluate and predict a whole class of preservice teachers' ability to succeed on the science domain IV EC-6 TExES certification exam (Huang & Fang, 2013) Both forward MLR and BLR predictive models also included X1 as the first independent variable in the model. The Academics MLR and BLR model included grade in BIOL 1082 (X1), credits taking (X10), and current GPA (X13) and may also be useful in predicting performance in being the next best model with the smallest subset of independent variables. Uncontrolled Factors MLR and BLR models were not very good at predicting success, instead however the variable transfer (X3) within the model was a good predictor variable that could be used to identify individuals with transfer status as those which may be in the greatest need of remediation and intervention to help them prepare for their official EC-6 TExES certification examination.

The research findings gave rise to some important conclusions: (1) The best predictor of performance on the practice EC-6 TExES certification examination was the grade earned in BIOL 1082, Biology for Elementary Educators. (2) The independent variables transfer status (X3), Credits Taking (X10), and Current GPA (X13) individually also predicted performance and maintained statistical significance (3) The prediction accuracy for predicting passing the practice examination was between 30%-50% and predicting failure was at and above 78%. In both the MLR and the BLR predictive models, which included all 13 independent variables, explained the most variation and had the highest prediction accuracy in terms of performance on the practice examination. In the case of this study, it was important to predict which EC-6 TExES preservice teachers were in danger of failing to stage interventions prior to their official certification examination at this university. However, we posit that these same tools can be used by other EPPs to predict their own student's preparedness for certification success.

Other EPPs could use the individual predictor model (X1) to predict performance of preservice teachers at the end of a semester when students have taken any science for educators' course. Additionally, a single preservice teacher's performance can be predicted using the Full MLR model and the Full BLR models because both MLR model explained the largest variation in the dependent variable and the BLR model yielded the largest prediction accuracy (Huang & Fang 2013). If the EPP does not have data for all 13 variables, the academics model can still predict performance with only three independent variables, grade in Science for Educators course (X1), credits taking (X10), and current GPA (X13). This model is the next best predictor of performance on the practice EC-6 TExES certification examination with the least number of variables.

Conclusions

Pursuing any type of degree or certification in tertiary education can be met with some type of financial pressure (Feuer et al., 2013). Additionally, in repeatedly failing their certification examination, preservice teachers can decrease the likelihood of starting a teaching career in a reasonable amount of time and may also result in the diminishing of confidences and the lessening of self-efficacy (Masters, 2018). Prediction of preservice teachers' performance on their certification examinations have been explored by other researchers (Hutson, 2018; Warren, 2017). However, no other study thus far looked at predicting the performance by preservice teachers on the science portion of their official EC-6 TExES certification examination. And most importantly, no other study has created predictive models for determining preservice teacher's success on the science portion of their EC-6 TExES certification exam.

In this study, variables that can possibly influence preservice teachers' performance on the science core of their EC-6 TExES certification examination were examined. Voluntary participants of this study were preservice teachers enrolled in BIOL 1082, is a mandatory science course EC-6 preservice teacher need to take in preparation for their official EC-6 TExES exam. This course covered almost half of the competencies preservice teachers need to be proficient in to successfully pass the official EC-6 TExES certification examination (TExES™ program preparation manual, 2019). The BIOL 1082 course included "clicker" questions over all the 18 competencies of Domain IV EC-6 TExES certification exam which were woven within each lesson taught to preservice teachers. Numerous hands-on lessons along with "think-pair-share" activities among others allowed for numerous opportunities for preservice teachers to learn concepts as well as conduct deep discussions on key topics. The practice exam was issued in the beginning of the semester of BIOL 1082 (pretest) and at the end of the semester (post-test). The Qualtrics™ survey was done online. The independent variables in this study were part of the survey which collected ex post facto, qualitative, and quantitative data from preservice teachers and the post-test score on the practice exam was the dependent variable of the study.

The creation of predictive models was conducted by use of multiple linear regression (MLR) and binomial logistic regression (BLR). The R^2, statistical significance and regression coefficient of each independent variable within each model were examined for the MLR models. For the BLR models the Nagelkerke R^2, the statistical significance, the odds ratio and the classification with prediction accuracy were examined. The results from the descriptive, MLR and BLR models analyses suggests that the Grade in BIOL 1082 (X1) is the most useful independent variable in predicting preservice teachers' performance on the science core of the practice EC-6 TExES certification examination.

The Academics model, which included the variables: grade in BIOL 1082 (X1), credits taking (X10), and current GPA (X13) for both the MLR and BLR predictive models were statistically significant and generally number of credits taking (X10), and current GPA (X13) trended toward an effect and toward increased chances of passing the practice exam. The only variable with statistical significance in the Uncontrolled Factors MLR and BLR models was transfer (X3) and revealed that transfer students' regression coefficient of -4.025 translated to the practice exam score prediction of 4.025 points lower for preservice teachers who transferred compared to those who had not. EPPs with information such as this may seek to offer more scaffolding and remediation to the preservice teachers that transfer into their program.

GPA, which in some studies have been shown to be a reliable predictor of students' performance, in that the GPA the range of 3.51 to 4.0 had the highest percentage pass at 55%. However, this trend did not continue in succession for the other GPA ranges. This correlation between GPA and success on practice exam could be strengthened if EPPs continue to maintain and improve the rigor of their curriculum to match the rigor of the TExES exam. Fine tuning of these efforts can be attained by collaboration between EPPs and TExES department to align curriculum tightly with expectations on the exit examination.

Though some of the predictors were not statistically significant within the model, their effect on the practice exam score were noticeable and, in some instances, had a small effect. Independent variable part-time (X9), revealed that these preservice teachers were less successful compared to those who were not. First-generation (X11) preservice teachers were less successful than their counter parts. The preservice teachers with a relative in education were more successful than those without. Preservice teachers who took college environmental science or college earth science classes (X7 and X8) generally trended with increased score or performance on the practice exam. For preservice teachers who took college physics (X6), while there was no direct increase in performance this variable seemed to act like a suppressor variable whose role is to indirectly impact the practice exam performance. Classification (X2) did not reveal sizeable differences between freshman, sophomores, and juniors' performance on the practice exam. However, preservice teachers classified as seniors who are most likely on the cusp of taking their official EC-6 TExES exam had the lowest performance on the practice exam with 0% passing the pretest and 15.40% of them passing the post-test. As such, the performance for seniors is crucial and should be prioritized. Having taken a college biology or chemistry class (X4 and X5) were associated with decreased performance on the practice exam which was also surprising but unfortunately what was missing from the survey questions and what was not revealed was where the preservice teachers took those courses and whether they had passed them.

Practice examinations have been shown to increase confidence and reduce anxiety of test takers (Bandura, 1997; Gard, 2011; Sullivan et al., 1996). EPPs could use practice examinations as a form of assessment which can provide insight as to preservice teachers' readiness for their certification examination as well as make available early interventions where needed. This practice certification examination may be used by EPPs in all their mandatory courses to find out what gains, if any, are made by preservice teachers and may help canvas the unremitting visibility of students' readiness as they progressively move closer to taking their official examination. This can create transparency that is advantageous to both EPPs and preservice students as they map and document their preparedness for the official TExES exam.

The objective of the predictive models is to allow for well-timed content interventions, when required, by the identification of preservice teachers who may be in danger of failing the certification examination. Such knowledge allows preservice teachers the chance to receive backing and scaffolding of content in practices that increase teacher content knowledge. Both types of regression predictive models suggest EPPs can predict preservice teachers who may be at risk of failing their certification exam. The binomial logistic regression offers the "big picture" of the probability of a preservice teacher passing or failing the exam, and multiple linear regression will give a predicted score that reveals borderline students.

Predictive modeling is and has been commonly used in a variety of pursuits, including retail, healthcare, entertainment, manufacturing, cybersecurity, human resources, sports, politics, and weather for 20 plus years, but is far less commonly used in education. In fact, in education, the most common uses deal with student retention indicators (Al Sheeb, et al. 2019; Bird, et al., 2021; Hung, et al., 2019; Smith, et al., 2012). However, as this study shows, predictive modeling can play an invaluable role in teacher education preparation as well. As many other industries have realized, predictive modeling is a means by which one can tentatively see into the future to determine a potential outcome, and by which to make decisions about resource management. This study demonstrates that predictive modeling is just as effective in the field of teacher education and can serve to provide important information that can be used to aid our perspective student teachers on their journey to their future career.

Limitations

The data used in this study was obtained from the survey which was self-reported. Some factors that may affect preservice teachers' performance on the certification exam may not have been used in this study. Factors such as the use of psychological, emotional, and other abstract variables that may be difficult to quantify may play a crucial role in preservice teachers' ability to pass the practice examination and these variables were not included in the study (Huang & Fang, 2013). Factors such as technology, the amount of time spent on social media, learning methods, self-motivation, and intrinsic reward system, along with some recent factors that might have not yet been studied for their effects on students' performance. Additionally, the time frame between completion of BIOL 1082 and taking the official EC-6 TExES certification examination will not be the same for each student as the course BIOL 1082 can be taken at any time during the preservice teachers' enrollment in the EPP and memory decay varies from student to student.

Future Research and Suggestions

The findings of this study have valuable suggestions that may help EPPs to successfully identify preservice teachers who may need timely interventions before taking their official state certification examination. Previous studies explored possible factors that may influence students' performance on an examination however, there are limited studies that have been conducted on the performance of preservice teachers (Warren, 2017). In addition, the use of predictive modeling could be used with other mandatory science courses needed to complete the EPPs curriculum to make this study more generalized.

The mandatory science courses can be taken at any time during preservice teachers' tenure in the teacher preparation program (TPP). It is suggested that perhaps the order in which the courses are taken be rearranged to allow the courses that address the most competencies on the science portion of the official EC-6 exam, be taken closer towards the end of their program. A practice exam can be used to assess testing readiness.

The authors received no financial support for the research, authorship, and/or publication of this manuscript.

Ruthanne Thompson (Ruthanne.thompson@unt.edu) conducts research in three areas: pre-service science teacher education, science teacher retention, and undergraduate STEM retention. Dr. Thompson has 30+ publications including book chapters, textbooks, and research reports; is a University Distinguished Teaching Professor, and she and her lab have received two prestigious awards and over $15M in grant funding to support pre-service teacher education and STEM retention.

Naudin Alexis (naudinalexis@my.unt.edu) is a data analyst with Frisco ISD in Assessment and Accountability. She received a bachelor's degree in biology from Midwestern State University, a master's degree in biochemistry and molecular biology from the University of North Texas, and a Ph.D. in environmental science with focus in science education from the University of North Texas. Her research interests include scientific research in education and comparison of accountability standards between Education Preparation Programs (EPPs) and academic accountability for public school districts.

Pamela Esprivalo Harrell (pam.harrell@unt.edu) is a science educator whose research agenda demonstrates a continued focus on teacher quality. While at UNT, she worked with colleagues to launch one of the first three online teacher certification programs in the US that continues to enroll and graduate a high number of master's students. She received 32 grants totaling over $10M and served as Pl or CoPI for over $8M of grant funding. She created The Simply Outrageous Science Professional Development Program that served over 400 middle school science teachers, increasing their pedagogical knowledge and raising student achievement in high-need schools.

References

Alismail, H. A. (2016). Multicultural education: Teachers' perceptions and preparation. *Journal of Education and Practice, 7*(11), 139-146.

Acharya, B. R. (2017). Factors affecting difficulties in learning mathematics by mathematics learners international. *Journal of Elementary Education, 6*(2), 8-15.

Al Sheeb, B., Abdella, G.M., Hamouda, A.M., & Abdulwahed, M.S. (2019). Predictive modeling of first-year student performance in engineering education using sequential penalization-based regression. *Journal of Statistics and Management Systems, 22*(1), 31-50.

Bains, L. (2011). An Analysis OF TExES Sores: Evaluating Teacher Preparation at one Institution in the State of Texas. Unpublished doctoral dissertation, University of Houston, Houston, TX.

Bandura, A. (1997). *Self-efficacy: The exercise of control.* New York, NY: W. H. Freeman and Company.

Banks, T., Jackson, D., & Harper, B. (2014). Responding to the call to prepare highly effective teacher candidates in the United States: The curriculum redesign effort in advancing teacher education. *Higher Education Studies*, *4*(2), 9-18.

Binns, I. C., Casto, A. R., Polly, D., & Bickmore, S. T. (2020). Examining pre-service teachers' integration of science and literacy through trade books. *Electronic Journal for Research in Science and Mathematics Education*, *24*(2), 7-21.

Bird, K.A., Castelman, B.L., Mabel, Z., & Song, Y. (2021). Bringing Transparence to Predictive Analytics: A systematic Comparison of Predictive Modeling Methods in Higher Education. *AERA Open, 7*.

Boyd, D., Goldhaber, D., Lankford, H., & Wyckoff, J. (2007). The effect of certification and preparation on teacher quality. *The Future of Children*, *17*(1), 45-68.

Capraro, R. M., Capraro, M. M., Parker, D., Kulm, G., & Raulerson, T. (2005) The Mathematics Content Knowledge Role in Developing Preservice Teachers' Pedagogical Content Knowledge. *Journal of Research in Childhood Education*, *20*(2), 102-118.

Chao-Ying, J. P., & Tak-Shing H. S. (2002). Logistic regression analysis and reporting: A primer. *Understanding Statistics, 1*(1), 31-70.

Collister, B. & Ellis, J. (2015). Central Texas teachers often struggle becoming certified. KXAN Investigates. http://kxan.com/investigative-story/central-texas-teachers-often-strugglebecoming-certified.

Cook, P. R. (2018). *An Exploration of Educational Trends (V2): A Symposium in Belize, Central America,* 110-115

Corcoran, R. P., & O'Flaherty, J. (2018). Factors that predict pre-service teachers' teaching performance. *Journal of Education for Teaching*, *44*(2), 175-193

D'Amico, M.M., & Dika, S.L. (2013). Using data known at the time of admission to predict first-generation college student success. *Journal of College Student Retention: Research, Theory & Practice, 15*(2), 173-192.

Darling-Hammond, L., Bae, S., Cook-Harvey, C.M., Lam, L., Mercer, C., Podolsky, A., & Stosich, E. L. (2016). Pathways to New Accountability Through Every Student Succeeds Act *Learning*

Policy Institute. Retrieved from https://learningpolicyinstitute.org/sites/default/files/product-files/Pathways_New-Accountability_Through_Every_Student_Succeeds_Act_04202016.pdf

Darling-Hammond, L. (2019). *A license to teach: Building a profession for 21st century schools*. Routledge.

DeFreitas, S. C. & Rinn, A. (2013). Academic achievement in first generation college students: The role of academic self-concept. *Journal of the Scholarship of Teaching and Learning, 13*(1), 57-67.

Donovan, C. B., Ashdown, J. E., & Mungai, A. M. (2014). A new approach to educator preparation evaluation: Evidence for continuous improvement? *Journal of Curriculum and Instruction*, *8*(1), 86-100.

Douglass, J., & Thomson, G. (2012). Poor and rich: Student economic stratification and academic performance in a public research university system. *Higher Education Quarterly, 66*(1), 65-89.

Every Student Succeeds Act, 20 U.S.C. § 6301 (2015). https://www.congress.gov/bill/114th-congress/senate-bill/1177

Feuer, M. J., Floden, R. E., Chudowsky, N., & Ahn, J. (2013). Evaluation of Teacher Preparation Programs: Purposes, Methods, and Policy Options. National Academy of Education. 500 Fifth Street NW Suite 339, Washington, DC 20001.

Frizzell, M., & Moffett, N.L. (2014). The Identification of Variables and Factors Related to Preservice Teacher Candidates' Passing a State Teacher Certification Examination at an HBCU.

Gard, D. R. (2011). *Teacher Certification Exams: Predicting Failure on the TExES History (8-12) Content Exam (A Nonparametric Approach using Classification Trees).* Unpublished doctoral dissertation, Texas Tech University, Texas.

Graunke, S.S., & Woosley, S.A. (2005). An exploration of the factors that affect the academic success of college sophomores. *College Student Journal, 39*(2), 367-377.

Hosmer, D.W. & Lemeshow, S. (2000). *Applied logistic regression* (2nd edition). John Wiley & Sons, Inc., New York. doi:10.1002/0471722146

Huang, S., & Fang, N. (2013). Predicting student academic performance in an engineering dynamics course: A comparison of four types of predictive mathematical models. *Computers & Education, 61*, 133-145.

Hung, J.L., Shelton, B.E., Yang, J., & Du, X. (2019). Improving predictive modeling for at-risk student identification: A multistage approach. *IEEE Transactions on Learning Technologies, 12*(2), 148-157

Hutson, T. (2017). Preparing for EC-6 Teacher Certification in Texas: How much Science is Enough? In P. R. Cook (Ed.), *An Exploration of Educational Trends (V2): A Symposium in Belize. Central America* (pp.111-120). United Kingdom: Cambridge Scholars Publishing.

Hyndman, R. J. and Koehler, A. B. (2006). Another look at measures of forecast accuracy. *International Journal of Forecasting*, *22*(4), 679-688.

Karamazova, E., Zenku, T. J., & Trifunov, Z. (2017). Analyzing and comparing the final grade in mathematics by linear regression using Excel and SPSS. *International Journal of Mathematics Trends and Technology (IJMTT), 52*(5), 334-344.

Kazempour, M., & Sadler, S. D. (2015). Pre-service teachers' science beliefs, attitudes, and self-efficacy: a multi-case study. *Teaching Education, 26*(3), 247-271.

Khajuria, S. (2007). *A model to predict student matriculation from admissions data.* Unpublished master's thesis, Russ College of Engineering and Technology, Ohio University, Ohio.

Kim, E., & Corcoran, R. P. (2018). Factors that influence pre-service teachers' persistence. *Teaching and Teacher Education*, *70*, 204-214.

Krieg, J.M. (2010). Academic performance of native and transfer students.

Kuha, J., & Mills, C. (2017). On group comparisons with logistic regression models. *Sociological Methods & Research*. ISSN 00491241

Lesley, E. L. (2016). What parents still do not know about No Child Left Behind and why it matters. *Journal of Education Policy*, *31*(3), 343-361.

Linn, V., & Jacobs, G. (2015). Inquiry-based field experiences: transforming early childhood teacher candidates' effectiveness. *Journal of Early Childhood Teacher Education*, *36*(4), 272-288.

Lykourentzou, I., I. Giannoukos, G. Mpardis, V. Nikolopoulos, & V. Loumos. (2009). Early and dynamic student achievement prediction in e-learning courses using neural networks. *Journal of the American Society for Information Science and Technology*, *60*(2), 372-380.

Martinez, J.A., Sher, K.J., Krull, J.L., & Wood, P.K. (2009). Blue-collar scholars?: Mediators and moderators of university attrition in first-generation college students. *Journal of college student development, 50*(1), 87.

Masters, G. (2018). The role of evidence in teaching and learning. *Australian Council for Educational Research*, *4*, 3-5.

Miller, S. P & Hudson, P. J. (2007). Using evidence-based practices to build mathematics competence related to conceptual, procedural, and declarative knowledge. *Learning Disabilities Research and Practice*, *22*(1), 47-57.

Murphy, C., Neil, P., & Beggs, J. (2007). Primary science teacher confidence revisited: ten years on. *Educational Research*, *49*(4), 415-430.

Murphy, C., & Smith. G. (2012). The impact of a curriculum course on pre-service primary teachers' science content knowledge and attitudes towards teaching science. *Irish Educational Studies*, *31*(1), 77-95.

NCES. (2017). The Condition of Education. Washington, D.C.: National Center for Educational Statistics.

NCTQ. (2014). Teacher Prep Review. Washington, D.C.: National Council on Teacher Quality.

Peters, B. A., & Draughon, G. B. (2017). Part-Time Students and Performance-Based Funding 2.0 in United States Public Higher Education. In H. Alphin, Jr., J. Lavine, and R. Chan (Ed.), Disability and Equity in Higher Education Accessibility (pp. 153-176). IGI Global. http://doi:10.4018/978-1-5225-2665-0.ch007

Pino-Pasternak, D., & Volet, S. (2018). Evolution of pre-service teachers' attitudes towards learning science during an introductory science unit. *International Journal of Science Education*, *40*(12), 1520-1541.

Sandholtz, J. H., & Shea, L. (2015). Examining the Extremes: High and Low Performance on a Teaching Performance Assessment for Licensure. *Teacher Education Quarterly,* 42(2), 17–42.

Sasson, I. (2014). The role of informal science centers in science education: Attitudes, skills, and self-efficacy. *Journal of Technology and Science Education*, *4*(*3*), 167-180.

Senler, B. (2016). Pre-service science teachers' self-efficacy: The role of attitude, anxiety, and locus of control. *Australian Journal of Education*, *60*(1), 26-41.

Shipe, M. E., Deppen, S. A., Farjah, F., & Grogan, E. L. (2019). Developing prediction models for clinical use using logistic regression: an overview. *Journal of thoracic disease*, *11*(4), 574–584. https://doi.org/10.21037/jtd.2019.01.25

Smith, T.J., & McKenna, C.M. (2013). A comparison of logistic regression pseudo R2 indices. *Multiple Linear Regression Viewpoints, 39*(2), 17-26.

Smith, V.C., Lange, A., & Huston, D.R. (2012). Predictive modeling to forecast student outcomes and drive effective interventions in online community college courses. *Journal of asynchronous learning networks, 16*(3), 51-61.

Sperandei, S. (2014). Understanding logistic regression analysis. *Biochemia Medica*, *24*(1), 12-18.

Stroud, J. C., Smith, L. L., Ealy, L. L., & Hurst, R. (2000). Choosing to Teach: Perceptions of Male Preservice Teachers in Early Childhood and Elementary Education. *Early Child Development and Care*, *163*(1), 49-60.

Sullivan, W. G., Daghestani, S. F., & H. R. Parsaei. (1996). Multivariate analysis of student performance in large engineering economy class. *Technology-Based Re-Engineering Engineering Education Proceedings of Frontiers in Education FIE'96 26th Annual Conference*, *1*, 180-184.

Sutcher, L., Darling-Hammond, L., & Carver-Thomas, D. (2016). *A coming crisis in teaching? Teacher supply, demand, and shortages in the U.S.* Palo Alto, CA: Learning Policy Institute., 1-16. Retrieved May 17, 2018, from https://learningpolicyinstitute.org/sites/default/files/product-files/A_Coming_Crisis_in_Teaching_BRIEF.pdf

Swecker, H. K., Matthew, F., & Searby, L. (2013). Academic advising and first-generation college students: A quantitative study on student retention. *NACADA Journal*, *33*(1), 46- 53.

Texas Education Agency (TEA). (2018). *Educator certification.* Retrieved from http://tea.texas.gov/Texas_Educators/

Thobega, M, & Miller, G. (2008). Predicting Scores of Beginning Agricultural Education Teachers on the Praxis II Examination. *Journal of Agricultural Education*, *49* (1), 99–109.

Van Aalderen-Smeets, S. I., Van der Molen., Van Hest, J. H. W., & Poortman, C. (2017). Primary teachers conducting inquiry projects: effects on attitudes towards teaching science and conducting inquiry. *International Journal of Science Education*, *39*(2), 238-256.

Warren, S. (2017). *The relationship between admission criteria and TExES Generalist EC-6: An archival study of predictors of future success in the teacher preparation program at a historical black college in Southwest Texas.* Unpublished doctoral dissertation, North Central University, Minneapolis, MN.

Yang, S. J. H., Lu, O. H. T., Huang, A. Y. Q., Huang, J. C. H., Ogata, H., & Lin, A. J. Q. (2018). Predicting students' academic performance using multiple linear regression and principal component analysis. *Journal of Information Processing*, *26*, 170-176.

Appendix A

Biology for Educators Survey

Q1 Last name

____

Q2 First name

____

Q3 Student ID number

____

Q4 UNT Email address

____

Q5 Gender

- ☐ Male
- ☐ Female
- ☐ Do not wish to share

Q6 Age

- ☐ 18-20
- ☐ 21-23
- ☐ 24-26
- ☐ 27-30
- ☐ 31-35
- ☐ 36-40
- ☐ 40+

Q7 What is your current classification?

- ☐ Freshman
- ☐ Sophomore
- ☐ Junior
- ☐ Senior
- ☐ Post Baccalaureate
- ☐ Graduate student
- ☐ Other ____

Q8 From the following choices, please select the type of high school you attended. In the box under the type of high school, please write the name of the high school, and the school district if applicable.

- ▢ Public school ____________________
- ▢ Private school ____________________
- ▢ Boarding school ____________________
- ▢ Home schooled

Q9 Check the box next to all the science courses you have taken in high school. If some of the science course/s were taken at a different high school/s, write name of school next to the name of the science course. If applicable, indicate if the course was an honor/advanced placement course in the box next to the science course. If the course is not listed, please check the box "other" and write the name/s of the course/s in the box.

- ▢ Biology ____________________
- ▢ Chemistry ____________________
- ▢ Physics ____________________
- ▢ Environmental science____________________
- ▢ Aquatic science ____________________
- ▢ Forensic science ____________________
- ▢ Earth science ____________________
- ▢ Agriculture ____________________
- ▢ Marine biology ____________________
- ▢ Botany ____________________
- ▢ Zoology ____________________
- ▢ Other ____________________

Q10 Are you a transfer student? If so, please state the college and/or university you transferred from. continue to the following question to select the science courses you have taken at the college level prior to attending UNT.

- ▢ Yes____________________
- ▢ No

Q11 If you have transferred from a college and/or university, please select from the list below the science courses you have taken there. If applicable, please write the name of college or university where the course was taken in the box next to the course

- ▢ Biology ____________________

- ☐ Chemistry ____________________
- ☐ Physics ____________________
- ☐ Environmental science ____________________
- ☐ Aquatic Science ____________________
- ☐ Forensic science____________________
- ☐ Earth science ____________________
- ☐ Agriculture ____________________
- ☐ Marine biology ____________________
- ☐ Botany ____________________
- ☐ Zoology ____________________
- ☐ Other ____________________

Q12 Check the box next to all science courses that you have taken at UNT prior to taking this class. State the name of college where the science course/s was taken next to the science course. If applicable, indicate if the course was an honor/advanced placement course in the box next to the science course. If the course is not listed, please check the box "other" and write the name/s of the course/s in the box.

- ☐ Biology ____________________
- ☐ Chemistry ____________________
- ☐ Physics ____________________
- ☐ Environmental science ____________________
- ☐ Aquatic Science ____________________
- ☐ Forensic science____________________
- ☐ Earth science ____________________
- ☐ Agriculture ____________________
- ☐ Marine biology ____________________
- ☐ Botany ____________________
- ☐ Zoology ____________________
- ☐ Other ____________________

Q13 List the science courses that you are currently enrolled in while taking this class. If the course is not taken at UNT, please write the name of the college next to the course. If applicable, indicate if the course is an honors course.

- ☐ Course 1 ____________________

▢ Course 2 ____

▢ Course 3 ____

▢ Course 4 ____

▢ Course 5 ____

Q14 Are you a part-time or a full-time student? List the number of credits you are currently taking next to your choice.

▢ Part time ____

▢ Full time ____

Q15 Are you a first-generation college student? Meaning are you the first member of your family to attend college?

Optional: If no, please state your relationship to the person who previously attended.

▢ Yes

▢ No ____

Q16 Do you have a parent and/or a close relative who obtained a degree in Education?

▢ Yes ____

▢ No

Q17 Why did you decide to pursue an Education degree?

____

Q18 What grade level do you plan on teaching?

____

Q19 Have you taken this class before? If yes, what grade did you receive and what is the reason for retaking this class?

o Yes ____

o No

20 What is your current GPA?

▢This is permission to access your GPA from the Office of Institutional Research at UNT. Write your first name and last name in box below for full consent.

____

▢ GPA can be accessed at my.unt.edu

____

Q21 Check the box of the standardized tests listed below that you have taken. Write the score you obtained (to the best of your recollection) in the space under the name of the test.

▢This is permission to access any of the below scores that are available from the Office of Institutional Research at UNT. Write your first name and last name in box below for full consent.

____

☐ ACT or SAT ____

☐ GRE ____

☐ TAKS or STAAR (science portion) or if high school is out Texas, the equivalent end of course exit exam ____

☐ Other? Write the name of the test and score (optional) below.
____