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Statistical Models of Self-Efficacy in STEM Students

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Abstract

Persistence through undergraduate education may be explained by self-efficacy. It is the belief in one's self to persevere through challenges. Bandura stated four areas that are thought to influence self-efficacy: mastery experience, social persuasion, vicarious experience, and physiological state. In this study, we focused on general and academic self-efficacy in STEM students, in the hopes of learning more about the relationships between Bandura's categories, demographics, and self-efficacy. Data was taken from two institutions: one, a large research focused university, and the other, a smaller teaching focused university. In the first phase, surveys on general self-efficacy were taken at both institutions by 118 students. In the second, academic self-efficacy data was taken from 599 students. These surveys included questions concerning demographics, Bandura's categories, and self-efficacy. Scores were summed for constructs relating to one of Bandura's four categories. We used Cronbach's alpha as a measure of internal reliability within each of the constructs. Correlation and linear regression analyses were used to study the data. Dummy variables for demographic data were created and used in the regression models. The best model found for general self-efficacy, including all phase 1 constructs and dummy variables, has an R^2 value of 0.558. For academic self-efficacy, our best model includes all constructs and dummy variables and has an R^2 value of 0.526. The goal of this work is to find factors that may potentially influence self-efficacy, in the hopes that they may be used in further research aimed at ensuring persistence of STEM students.

Introduction

The growing need for qualified workers in science, technology, engineering, and mathematics (STEM) fields will not be met by current anticipated university graduates. A study from 2010 on persistence in STEM degrees, using data from the National Student Clearinghouse that followed 2004 entering freshmen, found that only 24.5% of white students and 32.4% of Asian American students who declared a STEM major as freshmen completed a STEM degree in four years (Chang, 2010). The situation is even worse with underrepresented groups. The same study found that “Latino, Black, and Native American students … had four-year STEM degree completion rates of 15.9%, 13.2%, and 14.0%, respectively” (Chang, 2010). This is startling, considering the demand for STEM positions is expected to increase. In order to ensure a strong workforce of scientists and engineers in the future, one must understand why the levels have fallen so low.

We know of several factors that may influence students’ perseverance in STEM programs. In Anderson’s Force Field Analysis of College Persistence (Swail, 1995), positive and negative factors, both internal and external, give a picture of what it is that influences a student’s academic retention. External factors include exposure to educated individuals, knowledge of the benefits of receiving a college education, general knowledge of attending college, role within family, and employment situation (Swail, 1995). Internal factors include “identification with college educated persons”, academic preparation, self-confidence, self-doubt, and personal interests and motivations (Swail, 1995).

Many of the factors listed above are related to self-efficacy. Self-efficacy is defined as “people’s beliefs about their capabilities to produce designated levels of performance that exercise influence over events that affect their lives” (Bandura, 1994). Related to “perceived control, outcome expectations, perceived value of outcomes, attributions, and self-concept” (Schunk, 1991), it may have an effect on academic performance, as suggested in many studies (Bandura, 1994; Bong, 2003; Schunk, 1991; Zimmerman, 1992).

Much of the current work done on self-efficacy can be attributed to Albert Bandura. In defining self-efficacy, he stated four categories that are thought to be influencing factors: mastery experiences, social persuasion, vicarious experiences, and physiological state (Bandura, 1994). Mastery experiences are those successes one has experienced previously, making them more likely to succeed later. Having others’ encouragement or discouragement in achieving goals is social persuasion. Seeing a peer succeed or fail at a task is a vicarious experience. And physiological state is the level of physical ability of a person to complete a task. The work of Bandura and these categories were used to frame this study.

The main goal of this study is to find things that influence the generalized and academic self-efficacy of STEM students. We look at relationships and linear models of self-efficacy using constructs that pertain to STEM undergraduates which fall under Bandura’s previously stated categories. In this paper we look at previous work on academic retention, self-efficacy, and methods of social science research, giving more insight into their close relationship and how it frames this study. Then, we state our approach for data collection and analysis, and the results found. Finally, we discuss what this means for the field and work that may build upon the results.

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Background

The background work used for this study looks at resilience and persistence in education, self-efficacy, and social science analytical methods.

Resilience and Persistence

Work done on resilience and persistence in education identifies a variety of influences. Oscar Lenning stated a multitude of factors taken from previous studies that give a well-rounded picture of what influences student persistence (Swail, 1995). These include demographics (gender, ethnicity, social class, age), previously quantified academic achievements (test scores, grades, subject level achieved), goals and motivations, internal values (self-concept, maturity), institutional factors (size, prestige, services), and interactive factors (peer interactions, campus involvement, faculty interactions, familial and collegiate relationships) (Swail, 1995).

It has been shown that being a part of an underrepresented group has a negative effect on completing a degree in STEM fields. It seems that interest of African Americans and Hispanics in STEM is comparatively similar to that of Whites and Asian Americans as first-year college students, but when it comes to completion, minorities fall behind (Anderson, 2006). The same can be said for women. A study by Adelman in 1998, taking data from an 11 year period, found that “retention of men was nearly 20% higher than that of women” (Malicky, 2003). When one looks at self-efficacy, these differences persist. Self-rated science, math, and engineering self-efficacy was lower in women than men of each racial category in a study by Leslie from 1998 (Malicky, 2010).

The other factors mentioned (goals, internal values, and interactive factors) are strongly related to self-efficacy as well. The relationship between prior grades, academic achievement, and academic goal setting is shown in a study by Bandura (Zimmerman, 1992). It found that prior grades influence parental goals for students, which influence students’ self-efficacy, which influence students’ personal goals, all of which influence final grades achieved (Zimmerman, 1992).

Self-concept is similar to self-efficacy in that perceived ability is extremely critical, and both have academic specific definitions (Bong, 2003). However, they are not the same. Where academic self-concept is “knowledge and perceptions about oneself in achievement situations”, academic self-efficacy is the “convictions for successfully performing given academic tasks at designated levels” (Bong, 2003). Where self-concept is competence, self-efficacy is confidence (Bong, 2003).

The interactive factors thought to influence persistence are also influential to self-efficacy. Social persuasion and vicarious experience are primary predicting factors of self-efficacy (Bandura, 1994), both dealing with interaction. Peer and faculty interactions are important in persistence and self-efficacy. Identifying with peers and seeing them succeed may be reflected as a vicarious experience. For women and minorities, this may be seeing other students or faculty within a similar group achieve high grades, salaries, or degrees. Having strong relationships with faculty is an example of social persuasion. Encouragement by superiors may instill a higher self-perceived ability at a task, which influences self-efficacy and persistence.

Self-Efficacy

In order to frame the goals and methods of this study, more must be known about current self-efficacy research. As mentioned before, the foundations of self-efficacy research is attributed to Albert Bandura. He stated the four major sources, the processes self-efficacy affects, effects of self-efficacy, and the development of self-efficacy (Bandura, 1994). In this study, the survey questions fall under the four categories of self-efficacy and include mastery experience, vicarious experience, social persuasion, and physiological state (Bandura, 1994). Things like *interactions with faculty* and *sense of belonging* fall under social persuasion. Questions about *current GPA* and *expected GPA* fall under mastery experiences.

Cognitive, motivational, affective, and selection processes are the ways in which self-efficacy "affect[s] human functioning" (Bandura, 1994). Cognitive processes deal with goal-setting (Bandura, 1994). This plays a role in academics in the sense that students with high self-efficacy should set higher standards for themselves, achieving higher grades. Motivational processes affect the causal-perceptions of failures and successes (Bandura, 1994). A student with low self-efficacy may see a bad grade as the effect of insufficient ability, whereas a student with high self-efficacy may see a bad grade as the effect of insufficient study time. These perceptions influence whether a student continues to put forth effort or gives up easily. Affective processes are those that deal with anxiety and stress (Bandura, 1994). The ability to control thought processes in stressful situations affects the level of stress and anxiety experienced (Bandura, 1994). A student with high self-efficacy should be able to deal with a stressful semester without getting so overwhelmed that they give up. If one is not able to cope with stress, the psychological begins to affect the physiological, and physiological state is one of the main indicators of self-efficacy (Bandura, 1994). Selection processes are the ways in which people choose lifestyle and activity (Bandura, 1994). With a lower perception of ability (lower self-efficacy), one may not take on challenging yet rewarding experiences, such as higher education.

Self-efficacy develops and changes throughout life (Bandura, 1994). Babies are not born with a sense of self. This develops in the first couple of years of life and is the first step towards self-efficacy (Bandura, 1994). Young children develop a sense of their capabilities with the help of family and parenting (Bandura, 1994). The influences of peers combine with family as children age and begin school (Bandura, 1994). Children now have others to compare to themselves socially, physically, and mentally. At the same time, school is a crucial part of self-efficacy development (Bandura, 1994). This is where academic self-efficacy starts, and if one experiences a low sense of academic capability as a child, it is difficult to reverse (Bandura, 1994). As children move into adolescence and adulthood, self-efficacy alters and solidifies (Bandura, 1994). "Experimentation with risky behavior", lifestyle choices, and career paths are important to adolescent development (Bandura, 1994). Marriage, parenthood, and careers are important to adult development (Bandura, 1994).

Previous work has examined general self-efficacy (GSE) and academic self-efficacy (ASE). The GSE scale, developed by Schwarzer, provides a more general look at self-efficacy, whereas the ASE scale, developed by Pintrich and DeGroot, provides a focused look at self-efficacy in academics (Wilson, 2012). Both scales contain items specific to the type of self-efficacy being measured (Wilson, 2012). Outcomes

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using the two tools allow one to connect self-efficacy to general psychology with the GSE scale, as well as to education with ASE scale.

The influences of persistence and retention in academics are interrelated with those of self-efficacy, as self-efficacy has an impact on choice of actions and activities. All of this was used in the framing of this study.

Analytical Methods

The last area of work used in this study is analytical methods. Since the subject falls into behavioral and social sciences, we used accepted methods of that field. In general, social science research looks at relationships or correlations in the data. Firstly, one must decide whether the data is interval in nature. Interval data is data that has an arbitrarily chosen origin (Stevens, 1946). It is not ranked like ordinal data or “zeroed” like ratio data (Stevens, 1946). It may have negative values and contains units (Stevens, 1946). In our case, we assume it is and therefore, use methods that look at relationships in interval data samples. Before looking at relationships, it is good to look at means and standard deviations. The mean of the sample gives an average of the responses with respect to a certain variable, and the standard deviation is the amount the data deviates from the mean. These give a starting point of what to expect as one proceeds into analysis.

Surveys are a common method of data collection in social science research, and the questions they contain are usually grouped into variables or constructs. In order to analyze data such as this, one must look at the internal reliability within the constructs before looking at the relationships between constructs. Cronbach’s alpha is the most widely used statistic. It is a number between zero and one, one being perfectly reliable. Good internal reliability has an alpha value of at least 0.5. The GSE and ASE scales have high Cronbach’s alpha internal reliability values: the GSE scale with a value between 0.76 and 0.9, and the ASE scale with a value of 0.93 (Wilson, 2012).

A correlation test looks at the strength of relationships between the different variables, usually a target variable and those that are thought to be related. To quantify the relationships, Pearson’s Correlation Coefficient is typically used. It is a number between negative one and positive one: negative one being a perfect negatively correlated relationship, 0 being no relationship, and positive one being a perfect positively correlated relationship. Another method of looking at correlations in variables is regression modeling. The type of regression model used depends on the variables involved. A linear regression model is appropriate for linear relationships. A linear regression gives a linear equation which models the target variable in terms of the related variables. This is especially useful in research that looks at variables influencing another variable. The coefficient of determination (R^2) gives the percentage of variance in the modeled variable that may be attributed to the predictors. All of these statistical methods were considered in planning the analysis for this study. It is important to understand that a study such as this provides insight on a sample of data, not the population. The way the sample is chosen and the study is conducted decides how much one can say about the population. Therefore, the selection of the sample and its relationship to the population are important parts of the analysis. Also, the correlations do not imply causation; because two things are related does not mean one causes the other.

Methodology

This study was divided into two phases: Phase 1 looking at generalized self-efficacy (GSE), and Phase 2 looking at academic self-efficacy (ASE). In both phases, survey data was collected from undergraduate students in STEM courses at a primarily research-focused university in the Pacific Northwest (Research 1), and at a primarily teaching-focused university in the Midwest (Teaching). The two phases targeted different majors by surveying in certain department courses: Phase 1 included civil and environment engineering, electrical engineering, and computer science and Phase 2 included civil engineering, civil and environmental engineering, computer science, computer science and engineering, chemistry, mathematics, information systems and technology, and electrical engineering. Phase 1 contained constructs less related to academics, such as *Negative Affect* and *Positive Affect*, which describes student feelings and attitudes. Phase 2 contained constructs directly related to academics: *Affiliation with Global Workforce*, *Academic and Intellectual Development*, and *Belonging at Home University*. Both phases contained *Locus of Control*, types of *Belonging*, types of *Engagement*, *Interactions with Faculty*, *Mother's Education*, *Father's Education*, *Current GPA*, and *Expected GPA*. Details about the survey instrument can be found in Wilson et al. (2012).

Internal reliability of the constructs, relationships between constructs and self-efficacy, and linear regression modeling of self-efficacy were examined during analysis. We used the general self-efficacy (GSE) scale in phase 1 and the academic self-efficacy (ASE) scale in phase 2. In the survey, we used constructs that fall into Bandura's stated categories which influence self-efficacy. Our main goal was to find relationships between these constructs and the two type of self-efficacy. Assuming that the data was interval in nature, we chose to use a bivariate correlation test with Pearson's correlation coefficient to look at the linear relationships between self-efficacy, demographic information, and the constructs. Then taking the strength of the relationships into consideration, we attempted to model self-efficacy using the survey data with linear regression analysis. To incorporate demographics (gender, ethnicity, major, etc.), we created dummy variables for the linear regression models. We tried several linear regressions using different constructs in an effort to increase the coefficient of determination (R^2), giving a more reliable model. All the analysis was done in Microsoft Statistical Package for the Social Sciences (SPSS). The methods were the same for both phases.

Results and Analysis

In Phase 1, surveys were taken from 118 subjects (87 from Research 1 and 31 from Teaching). It included data from 102 males and 14 females. The surveys were taken in civil and environment engineering and electrical engineering courses at Research 1, and computer science and electrical engineering courses at Teaching. The majors given voluntarily by subjects matched the courses in which they were surveyed. Table 1 gives a breakdown of the frequencies, and means and standard deviations for GSE by groups.

Phase 2 looked at ASE and used data from 599 subjects (514 from Research 1 and 85 from Teaching). The subjects included 380 males and 191 females. The surveys were taken from students in civil engineering, civil and environmental engineering, chemistry, computer science, computer science and engineering, electrical engineering, information and technology systems, and mathematics courses. The majors varied from the course departments (e.g. biology, bio-chemistry, bio-engineering, and chemistry take the same chemistry courses). Table 2 gives numbers for frequencies, and means and standard deviations for ASE by groups. The sample distributions for both Phase 1 and Phase 2 were similar to the population (Wilson, 2012).

General self-efficacy tends to be higher amongst men than women and higher for Black and Hispanic students than Asian, Caucasian and Native American students (Table 1). The relationships across ethnic groups do not hold when measuring academic self-efficacy (Table 2). This is examined in detail in Wilson et al. (2012).

Table 1. Frequencies, means, and standard deviations for Phase 1

Category	Type	Sample Size N	GSE μ	GSE σ
Gender	Male (Female)	102 (14)	3.89 (3.77)	0.54 (0.59)
Institution	Research 1 (Teaching)	87 (31)	3.87 (3.88)	0.57 (0.46)
Ethnicity	Asian	34	3.65	0.54
	Black	4	4.37	0.55
	Caucasian	68	3.93	0.49
	Hispanic	3	4.78	0.25
	Native American	3	3.44	0.67
Area of Instruction (Research 1)	CEE (EE)	48 (39)	3.80 (3.96)	0.58 (0.56)
Area of Instruction (Teaching)	CS (EE)	18 (10)	3.90 (3.85)	0.54 (0.30)
Major	CEE	47	3.8	0.58
	EE	44	3.91	0.48
	CS	18	3.9	0.54

In Phase 1, most constructs (or bundles of questions related to the same concept) had acceptable internal reliabilities, as shown by Cronbach's alpha values over 0.5, as shown in Table 3. Constructs that related most strongly to a sense of belonging were initially targeted for evaluation and tended to be reliable (Belonging to Class, Connection to Major, Psychological Sense of Community, Interactions with Faculty, Positive Affect, Negative Affect, and Generalized Self-Efficacy). In Phase 2, the internal reliabilities, shown in Table 4, were higher than most in Phase 1 in the originally targeted constructs (Belonging, Belonging at Home University, Connection with Peer Group, Faculty Concern for Students, Emotional Engagement, and Academic Self-Efficacy). The exception was Emotional Engagement; we could not find any cause for the negative alpha. Constructs with positive alpha values were used in further analysis with regression models.

Table 2. Frequencies, means, and standard deviations for Phase 2

		N	ASE μ	ASE σ
Gender	Male(Female)	380(191)	3.62(3.18)	0.80(0.81)
Institution	Research 1(Teaching)	514(85)	3.44(3.67)	0.81(0.88)
Ethnicity	White	309	3.62	0.78
	Black	13	3.6	0.85
	Asian	202	3.28	0.86
	Native American/ Alaska Native	3	3.33	0.44
	Hispanic	16	3.29	0.65
	Other	28	3.34	0.86
Area of Instruction	CE	20	3.95	0.6
	CEE	81	3.53	0.71
	CHEM	236	3.24	0.84
	CS	42	3.56	0.95
	CSE	36	3.88	0.63
	EE	159	3.6	0.78
	ITSYS	10	4.05	0.67
	MATH	13	3.31	1
Major	Bio E	8	3.5	0.72
	BioChem	32	3.67	0.77
	Biology	87	3.05	0.76
	CE	20	3.95	0.6
	CEE	58	3.39	0.7
	Chem	26	3.3	0.84
	CS	51	3.81	0.74
	CSE	2	2.33	0.47
	EE	139	3.7	0.77
	IE	11	3.33	0.75
	Math	13	3.17	0.93
	ME	9	4.11	0.57

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Table 3. Cronbach's alpha values for Phase 1 constructs

Construct	Alpha
Belonging to Class*	0.418
Connection to Major*	0.655
Psychological Sense of Community*	0.617
Interactions with Faculty*	0.675
Positive Affect*	0.725
Negative Affect*	0.697
Generalized Self-Efficacy*	0.78
Classroom Engagement	0.509
Perceived Value of Engineering	0.662
Locus of Control	0.529

*Initially targeted for analysis

Table 4. Cronbach's alpha values for Phase 2 constructs

Construct	Alpha
Belonging*	0.904
Belonging at Home University*	0.869
Connection with Peer Group*	0.562
Faculty Concern for Students*	0.752
Emotional Engagement*	-0.025
Academic Self-Efficacy*	0.898
Affiliation with Global Workforce	0.814
Locus of Control	0.703
Interactions with Faculty	0.856
Academic and Intellectual Development	0.172
Institutional and Global Commitments	-0.154
Behavioral Engagement	0.218
General Course Objectives	0.84
Metacognitive Strategies	0.705

*Initially targeted for analysis

We analyzed correlation in order to identify variables with the strongest relationships as predictors for self-efficacy in the regression analysis, with the expectation that the more strongly correlated constructs would be better predictors. However, none of the correlations in either Phase 1 or Phase 2 have a Pearson's Correlation Coefficient at or above $|0.5|$. The results for the bivariate correlation tests are given for Phase 1 in Table 5 and in Table 6 for Phase 2.

Table 5. Pearson's correlation coefficients for variables and GSE in Phase 1

Variable	Pearson's CC	Variable	Pearson's CC
Current GPA	0.1	Positive Affect	0.269
Expected GPA	0.167	Negative Affect	-0.174
Classroom Experience	0.076	Advising Quality	0.176
Peer Interactions	0.086	Class Experiences	0.076
Mother's Education	-0.028	Fulfillment in Classes	-0.068
Father's Education	-0.147	Classroom Engagement	-0.082
Belonging to Class	0.234	Perceived Value of Engineering	0.416
Connection to Major	0.347	Locus of Control	0.427
Psychological Sense of Community	0.29	Age	0.204
Interactions with Faculty	0.03	Year in Program	-0.107

Table 6. Pearson's correlation coefficients for variables and ASE in Phase 2

Variable	Pearson's CC	Variable	Pearson's CC
Current GPA	0.32	Locus of Control	0.340
Expected GPA	-0.33	Interaction with Faculty	0.284
Mother's Education	0.71	Academic and Intellectual Development	0.257
Father's Education	0.41	Institutional and Goal Commitments	0.229
Belonging to Class	0.416	Behavioral Engagement	0.307
Belonging at Home University	0.218	Metacognitive Awareness	0.471
Connection with Peer Group	0.128	Metacognitive Strategy Use	0.320
Faculty Concern for Students	0.179	Age	0.140
Emotional Engagement	0.338	Year in Program	0.123

During regression analysis, we started with variables that possess stronger relationships with self-efficacy, using these in the first models for both Phases 1 and 2. Since that returned such low coefficients of determination (R^2), we decided to keep adding more variables to increase the reliability: first the originally targeted variables and then the remaining variables. The originally targeted variables for both phases are indicated by * in Tables 3 and 4, along with Current GPA, Expected GPA, Mother's Education, and Father's Education. The additional variables for Phase 1 include: Advising Quality, Class Experiences, Fulfillment in Classes, Classroom Engagement, Perceived Value of Engineering, and Locus of Control. In Phase 2, the additional variables include: Affiliation with Global Workforce, Locus of Control, Interaction with Faculty, Academic and Intellectual Development, Institutional and Global Commitments, Behavioral Engagement, Metacognitive Awareness, and Metacognitive Strategy Use. The regression models tested with predictors and R^2 values for Phase 1 and Phase 2 are shown in Tables 7 and 8, respectively. The model with the best predictability in Phase 1 included all variables with an R^2 value of 0.587. In Phase 2, the model with the best predictability also included all variables with an R^2 value of 0.526.

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Table 7. Phase 1 linear regression models with predictors and respective R^2 values

Regression	Constructs used	R^2
1	Father's Education/ Belonging to Class / Connection to Major / Psychological Sense of Community / Positive Affect /Negative Affect/Current GPA/Expect GPA	0.194
2	Belonging to Class/Connection to Major/Psychological Sense of Community/Positive Affect	0.176
3	All initially targeted constructs (excluding gender and ethnicity)	0.259
4	Black/Native/Asian/Hispanic/Female	0.161
5	All initially targeted constructs (including gender and ethnicity)	0.328
6	All initially targeted constructs and additional (D10, D11, D12, C9, C12, C4)	0.419
7	All constructs (initially targeted and additional) and dummy variables (gender, ethnicity, area, major)	0.558
8	All constructs (initially targeted, additional, gender ethnicity, area, major, age, year in program)	0.587

Table 8. Phase 2 linear models with predictors and respective R^2 values

Regression	Constructs used	R^2
1	Current GPA/Expected GPA/Belonging/Emotional Engagement	0.29
2	Current GPA/Expected GPA/Belonging/Emotional Engagement/Connection with Peer Group/Faculty Concern for Students	0.286
3	All constructs (excluding dummy variables and additional constructs)	0.303
4	All constructs (including dummy variables and additional constructs)	0.526
5	All constructs (including dummy variables, additional constructs, age, and year in program)	0.499
6	Everything except Institutional and Global Commitments, Academic and Intellectual Development, Behavioral Engagement	0.522

Discussion and Future Directions

This study shows that the four sources described by Bandura are influential in self-efficacy but not the only things that matter in academic self-efficacy for STEM students. There are other factors at work that have not been considered. According to our results, the data only explains about 50% of the variability in Phase 1 for GSE and in Phase 2 for ASE. Although the constructs and scales used in this study have been shown to be valid, the correlation testing did not show significantly strong relationships. If the linear relationships are not strong, perhaps another type of relationship is present. If this is so, a regression model that matches the relationships would be necessary.

Our surveys dealt with sources of self-efficacy, but it seems that sometimes human functioning processes and self-efficacy development may in fact influence the individual's current state of self-efficacy also. Things like goal setting, the ways in which stress is handled, and personal perceptions of successes and failures may add to the model. These ideas should be considered moving forward.

In order to get a better picture of what is going on, we need to ask more questions about a wider variety of factors. What else is influencing self-efficacy? Perhaps looking at developmental self-efficacy may give more insight: have students with low self-efficacy developed an inferiority complex rooted in early academic experiences? Another approach may be doing qualitative research to examine student experiences in more depth and detail. Focus groups and interviews with students may bring forth other factors that were not used in the surveys of this study. A mixed-methods approach could be used where the results of the qualitative exploration, informed by the results presented here, would inform the creation of new surveys. The benefit of the quantitative results is the reliability that comes from a large sample size, but this is only useful if the questions address the factors that more fully explain the variability in self-efficacy seen across the sample size. The results from a survey instrument, informed by both this survey and qualitative research, should improve the predictability seen in linear regression models.

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Personal Biography

Sarah Painter is a junior, double-majoring in Mathematics and French. As an MSU student, she has worked as a tutor for the mathematics department and a research assistant for the computer science department, working with STEM education research. She has been involved with the MSU Honor's Program, MAX Scholar seminar, the math club, and the French club. She plans to enroll in a mathematics PhD program after graduating from MSU, in the hopes of becoming a mathematics professor.

Mentor Biography

Dr. Rebecca Bates is a professor in the Departments of Computer Science and Integrated Engineering. Her PhD in Electrical Engineering is from the University of Washington where she developed statistical modeling of pronunciation variation to improve automatic speech recognition. She has a degree in theological studies from Harvard Divinity School, an M.S. in Electrical Engineering from Boston University and a B.S. in Biomedical Engineering from Boston University. Current research projects include investigations of community and connection in STEM education, working on automatic speech recognition in noisy environments, and analyzing prosody in adolescents with Williams Syndrome. She is a 2011-12 AAAS Science and Technology Policy Fellow at the National Science Foundation.