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DEVELOPING A CAREER DEVELOPMENT ASSESSMENT FOR PREDICTING YOUNG STEM GRADUATES' EMPLOYABILITY AND CAREER BARRIERS

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ABSTRACT

DEVELOPING A CAREER DEVELOPMENT ASSESSMENT FOR PREDICTING YOUNG STEM GRADUATES' EMPLOYABILITY AND CAREER BARRIERS

Yi-Ching Lin
Old Dominion University, 2017
Director: Dr. Ginger S. Watson

The increased concern of declining STEM candidates could negatively impact the U.S. economy (Kelic & Zagnoel, 2009; Maltese & Tai, 2010). Previous studies suggest that the gap between the supply of STEM students in higher education and workface demand is not reflected merely in the number of STEM graduates but instead in the number of qualified STEM graduates who could satisfy STEM workforce demands (Kelic & Zagnoel, 2009; Lowell & Salzman, 2007). The current study used Rae's employability theory (Rae, 2007) to develop an assessment for evaluating student's career development in STEM during their higher education. Unlike other instruments focusing on students' interests, knowledge, and preparation of their careers interests, this new assessment integrated employability, enterprise, and curriculum elements to assess five career development domains. Results from an exploratory factor analysis indicated that the assessment retained four factors with a total of 33 questions. New STEM graduates' employment status, their skill development, work-based learning, and career management in STEM higher education were positively associated with their employment status (i.e., employed full-time or non-full-time). In addition, students' skill development, work-based learning, career management, and applied learning experiences significantly predicted their academic performance (i.e., GPA). The implications for this study support offering work-based curricula and personal-development opportunities in undergraduate STEM programs to help college students achieve their career goals in STEM, which could optimally decrease the skill gap between STEM higher education and workforce demands.

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This work is dedicated to my Father in Heaven and my family. Without Your inspiration, I would never have come to United States to study. Your supports sustained me for the past 10 years while I completed my graduate work and ultimately, my Ph.D. Especially when I was frustrated and struggled, your love helped me to pass trials and accomplish my goals.

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INTRODUCTION

The Great Recession of 2010 had a large impact on the United States economy, especially in the labor market. The U.S. based Society for Human Resource Management (SHRM) proposed that technology, globalization, cost containment, speed in market change, and the importance of knowledge capital significantly reshaped the U.S. workforce and workplace in the past decades (Rothwell & Kolb, 1999). The shift from the industrial era to the postindustrial era created a need for a knowledge-based economy, postsecondary education, and training as a pathway for both individual and company successes (Carnevale & Desrochers, 2003). Since 2006, Congress has stressed the importance of increasing Science, Technology, Engineering, and Mathematics (STEM) majors to meet 21st century workforce demands (Carnevale, Smith, & Melton, 2011; Hanushek, Peterson, & Woessmann, 2012). A recent report projected 210,000 new job vacancies by 2018 in STEM areas (Carnevale et al., 2011). Similarly, the Bureau of Labor Statistics (BLS) predicts that with newly created jobs and the retirement of the baby boomer generation, there will be more than three million STEM jobs that need to be filled by 2018 (Lacey & Wright, 2009; Maltese & Tai, 2011).

Therefore, the increasing demands for a STEM workforce will continue to gain attention in the United States (Carnevale, Smith, & Strohl, 2013). Although the number of students attending higher education (four-year institutions) has significantly increased from 524,000 in 1966 to 1,473,735 in 2006, only 16% of graduating students obtained STEM degrees in 2006 (NSF, 2010). Many researchers have expressed concern about the decline of STEM candidates in the U.S. educational system, which may impact the U.S. economy in the future (Kelic & Zagnoel, 2009; Maltese & Tai, 2010). There are many factors contributing to the gap between higher education supply and workforce demand in STEM fields. First, the percentage of students pursuing STEM majors decreased from 20% to 16% between 1996 and 2006 (Maltese & Tai, 2010; NSF, 2010). Specifically, the number of students with mathematics and physical science majors decreased from 3.8 % to 1.0 % between 1996 and 2006. On the other hand, the number of students majoring in computer science increased from 0.6% to 3.0% in the past three decades (Maltese & Tai, 2011). Based on the reports, the supply of STEM graduates is heavily influenced by the pull of demand incentives, such as earnings, job security, and working conditions (Carnevale et al., 2011).

Second, 36% of students who initially chose to pursue STEM degrees were no longer in STEM fields six years after their initial college entry, according a longitudinal study following 1,530 students in STEM majors (Chen, 2009). Similarly, in another study 46% of worker with Bachelor's degree in STEM left the STEM field in 10 years (Carnevale, Smith, & Melton, 2011). Researchers found that students who struggled to complete STEM majors or degrees in four years often chose other majors. Nearly 22% of those students ultimately dropped out of college after five years (Boundaoui, 2011). Specifically, 38% of students who start with a STEM major do not graduate (Carnevale, Smith, & Melton, 2011). According to another report, 19% of students who entered college receive a Bachelor's degree in a STEM major. Only 10% of STEM bachelor's graduates actually work in the STEM workforce and only 8% of STEM bachelor's graduates are still working in STEM 10 years following their graduation. Third, students report difficulty in making career decisions. According to a recent report, almost 50% of undergraduate freshmen in the United States reported no desire or an inadequacy to make career decisions (Hannah & Robinson, 1990; Stephen, 2010).

In contrast, many studies disagree that there is a shortage of STEM graduates entering the workforce. Studies by Kelic (2009) and Lowell's (2007) concluded that the education system produced a number of STEM graduates that far exceeded the STEM workforce demand. The rationale is that science and engineering occupations make up only about one-twentieth of all jobs. Therefore, each year there are three times more science and engineering four-year college graduates than available science and engineering positions for the students to fill (Kelic & Zagnoel, 2009; Lowell & Salzman, 2007). Another study investigated new graduates' employment situation, 43% of STEM new graduates do not work in STEM occupations (Carnevale, Smith, & Melton, 2011). Researchers suggested that deficiencies in students' science and engineering performance have resulted in insufficient requisite science and engineering workforce demand. In other words, the gap between STEM higher education supply and STEM graduate worker demand did not reflect the supply of available jobs, but instead represents the total number of qualified students who could satisfy job demands in the STEM workforce (Kelic & Zagnoel, 2009; Lowell & Salzman, 2007). The disagreements between supply of and demand for STEM workers could not be resolved by simply increasing the number of individuals with STEM degrees (Carnevale et al., 2011).

Statement of Problem

Previous studies were mainly focused on investigating factors influencing college students to choose and remain in STEM majors with the purpose of increasing the number STEM candidates in the educational system. The current study focused on investigating what factors could increase graduates' employability and close skill gaps between higher education and the workforce in STEM fields.

Research Hypotheses

The current study was guided by the following hypotheses:

Hypothesis 1: Student’s career development consists of five factors including personal development, applied learning, skill development, work-based learning, and career management.

Hypothesis 2: Students that utilized career services and took CTE courses have higher levels of career development and lower levels of career barriers.

Hypothesis 3: Students with different STEM majors have different levels of career development and career barriers.

Hypothesis 4: Individuals employed full-time in STEM have higher levels of career development and lower levels of career barriers.

Hypothesis 5: Student’s career development in STEM higher education will predict their career barriers in the STEM workforce.

Hypothesis 6: Student’s career development in STEM higher education will predict their employment status.

Hypothesis 7: Student’s career development in STEM higher education will predict their GPA.

Background

The issue of employability and skills gap in higher education is gaining more attention since the economic recession in 2010. Researchers found that college students’ degrees are not actively used, and many non-college degree jobs (high school degree jobs) are disappearing (BLS, 2002-2012). The unemployment rate for new college graduates increased from 5.4 to 10 percent in the United States in the same year. Although the rate gradually declined to 8 percent in

2013, new college graduates are still at a relatively high level of unemployment after the most recent economic recession.

To decrease the unemployment rate and prepare more qualified new graduates to meet workforce demands, the Obama Administration created a college “scorecard” to rate schools on their performance through evaluation of graduation rates and career outcomes. Currently, the federal government is using this measurement system to determine the amount of state tax dollars and federal student aid that should be given to higher education institutions (Morgan & Dechter, 2012; Collins, Jenkins, Strzelecka, Gasman, Wang, & Nguyen, 2014; Kurlaender, Carrell, & Jackson, 2016). Therefore, higher education institutions have been forced to pay more attention to students’ employment and salary outcomes than ever before.

Significance of the Study

In previous studies, researchers have explained what factors influence students to choose STEM majors. Social cognitive career theory (SCCT) is one of the most popular and well accepted theories for explaining what factors influence students choosing STEM majors. The theory is built upon Bandera’s general social cognitive theory (1986). The central mechanism of social cognitive career theory is self-efficacy. According to Bandura (1997), self-efficacy refers to students’ confidence in their ability to successfully perform a variety of academic tasks including academic performance, persistence, perceiving career options, coping with barriers, and solving problems in science and engineering majors. Therefore, self-efficacy determines human motivation, affect, and action, and is the best predictor of students’ ability to attain academic milestones and performance. The SCCT theory suggests that students’ academic and career-related interests are influenced by the interaction of personal, environmental, and behavioral variables (Lent, Brown, Sheu, Schmidt, Brenner, Gloster, Wilkins, Schmidt, Lyons, Treistman, 2005).

Wang's modified social cognitive career theory (2013) is based on a longitudinal study that investigated factors influencing students choosing STEM major from tenth grade to college. This study revealed several important findings. First, high school preparation in math and science played a critical role on students interested in pursuing and entering STEM majors. Second, students' math self-efficacy, exposure to math and science, and completion in math and science courses significantly predicted their intent to major in STEM fields as expressed during high school. Third, both students' intent to major in a STEM field and the completion of math and science courses significantly predicted students' entrance into STEM majors in college (Wang, 2013). Both Lent's and Wang's studies provide a comprehensive framework for explaining students' choosing STEM majors.

There are several unique contributions of the current study. First, Rae's theoretical framework is integrated employability and enterprise into curriculum design in higher education. However, originally Rae's theoretical model was for business schools and there was no assessment tool to measure students' career development. Therefore, researchers applied his model to develop a career assessment for assessing students' career development experiences particularly in STEM higher education. Second, researchers conducted a cross-sectional study and utilized the assessment to predict the relationships between students' career development in STEM higher education and their employability in STEM workforce later on. While other studies also directly assessed graduates' career barriers, the third contribution of the current study was focused on STEM degree programs how to support STEM college students' career and skill developments required to succeed in the STEM workforce. Fourth, unlike some studies that directly listed skills required of students in the 21st century, the current study grouped skills based on Rae's theoretical framework into five different domains/sub-scales for predicting students' employment status and career barriers in the workforce. The results of this work may provide guidance and evidence for promoting the integration of employability and enterprise into curriculum design particularly in STEM areas of study within higher education. The literature review provides a detailed description of Rae's theoretical framework. Finally, researchers utilized Markov Chain Monte Carlo (MCMC) techniques to validate models created in the current study.

This work summarized the significance of the current study including (1) the unique approaches of integrating employability, enterprise, and curriculum design developing and evaluating students' career development in STEM higher education, (2) using cross-sectional research design to test hypotheses, (3) building models for predicting new graduates' employment status and career barriers based on their career development in STEM higher education, and (4) using Markov Chain Monte Carlo (MCMC) simulation methods to validate models.

Imitations

The following limitations existed in the present study: This study only collected data from participants through emails (new STEM graduates) and instructors' announcements (current students) in the classes at a university. The result may not be representative of all students' experiences of career development in STEM higher education. In addition, the present study excluded the following participants (1) veteran, (2) military, (3) medical/health sciences related majors, (4) nonnative speakers, and (5) age above 26 years-old. Some current students who switched to other majors or dropped out from STEM majors, researchers were not able to get hold of them. Young STEM graduates were only recruited from those just graduated within six months but excluded those were going to graduated schools.

Assumptions

1. **Random sampling**: Each participant was randomly drawn from the population of interest.
2. **Multivariate normality**: The acceptable limits of skewness and kurtosis of data are ±1.96 which could be considered normally distributed (Trochim & Donnelly, 2006; Field, 2000; Gravetter & Wallnau, 2014).
3. **Bivariate normal distribution:** A pair of variables that are normally distributed.
4. **Linearity**: The relationships between variables are linear.

Procedures

This study developed an inventory for assessing students' career development in STEM higher education and predicting new graduates' employability and career barriers in the STEM workforce. Participants consisted of 109 senior-year students and 35 new graduates. The researcher recruited participants through several higher education instructors who allowed their students to participate in this study from biology, mathematics, computer science, physics, and engineering departments at a single southeast university in the southeastern United States.

Definition of Terms

The following terms and definitions will aid the reader in comprehending this study:

1. Career and Technical Education (CTE): It is a under umbrella organization from the Association for Career and Technical Education (ACTE). CTE was replaced vocational and technical education in 2006. According to the most recent reauthorization Perkins Act of 2006 (Brustein, 2006), career and technical education is

organized educational activities that offer a sequence of courses with coherent and rigorous content aligned with academic standards and relevant technical knowledge and skills which are needed to prepare students for further education and careers in current or emerging professions. It also offers technical skill proficiency, an industry/business-recognized credential, a certificate, or an associated degree. Most career and technical education programs are offered at the secondary and post-secondary levels with courses in seven specific labor market program areas including agriculture, business and information technology (formerly business education), family and consumer sciences (formerly home economics), marketing (formerly distributive education), health, trade and industry (T&I), and technical/communications.

2. Career barriers: Events or conditions, either with the person or environment, which make career progress difficult (Swanson & Woitke, 1997; Stephen, 2010).
3. Career development model: Originally the model includes personal development, applied learning, skill development, work-based learning, and career management (Rae, 2007). In the current study, researchers modified the model into four factors including skill development, work-based learning, career management, and applied learning.
4. Enterprise: There are many definitions of enterprise in the academic context. Based on Rae's definition, enterprise the skills, knowledge and attributes needed to apply creative ideas and innovations to practical situations. For example, initiative, independence, creativity, problem solving, identifying and working on opportunities, leadership, and acting resourcefully and responding to challenges (Rae, 2007).

5. Employability: It is a set of skills, knowledge and personal attributes that make an individual more likely to secure and be successful in their chosen occupation to the benefit of themselves, the workforce, the community and the economy (Moreland, 2006; Rae, 2007).
6. New graduates: Students that graduated from a college/university within six months and were under 26 years old.
7. STEM: Science, technology, engineering, and mathematics (Maltese & Tai, 2010; NSF, 2006). In the present study, STEM is referred to five different majors including biology, mathematics, computer science, physics, and engineering.
8. Work Placement: The temporary posting of someone in a workplace to enable him or her to gain work experience (Dictionary, 2004).

CHAPTER II

REVIEW OF LITERATURE

Undergraduate employability was not a major concern for higher education until the number of students attending higher education drastically increased in the past decades. Today, undergraduate employability has been one of the primary indicators for evaluating a university's performance in many developed nations. Specifically, high school and university started to offer competitive courses and degrees for attracting students when economic downturns focused attention on unemployment and underemployment. Recently there are many strategies to enhance new graduates' employability in secondary and post-secondary educations.

Career Technical Education

The name of vocational and technical education was replaced with career and technical education (CTE) in 2006. Today CTE is not only for students learning skills required in workforce, but also provide students to earn credentials and certifications, and associate degrees. CTE is preparing students for careers required non-college and college. In addition, CTE at all levels (high school, technical school, community college, and university) enhances academics by bringing real-world context and application to education. The curriculum of Career and Technical Education combines academic rigorous and career relevant for helping students to succeed in various careers and professions. It focuses on helping students to apply their learning to different contexts (business, industries etc.) through school projects, internships, or working experiences. The result of practicing new curriculum increases academic standards and rigorous to improve teaching and outcomes which enhance students' competitiveness in workplace and postsecondary education (Brustein, 2006).

Although career and technical education (CTE) provides career pathways for encouraging and preparing students to either enter the STEM workforce at high school, technical school, community college, and university, CTE is not a common part of the 4-year university system in the United States. In a dual educational system, the non-university sector focuses on preparing students for career development and meeting workforce demands within a specific area of study, with most students coming from secondary and two-year postsecondary vocational education systems. In contrast to a dual system, 4-year university often provide career development services and career counseling to facilitate students' career decisions. Career service centers in higher education are responsible for both knowing the desired career destinations of students and leading graduating students into the best possible jobs (Koc & Tsang, 2015).

Career Service in Higher Education

Today career services in colleges are a well-accepted strategy for strengthening students' career choices and career preparation in universities. For instance, a university carrier service training program for helping students choosing career, creating the resumes, finding internship and job opportunities in the career service center. However, the career services are separate structures from the academic colleges and students are not required to utilize them in accordance with the curricula of most universities (Kyvik, 2004; Rae, 2007). The lack of a clear link between skills covered in academic courses and employers' skill demands may influence new graduates' employability and increase skills gap between higher education and workforce demand (Rae, 2007).

New Vocationalism

The new trend of refocusing on employability in higher education has caused students to become more selective in their choices of courses and institutions. The definition of employability is a set of skills, knowledge, and personal attributes that make an individual more likely to secure a job and be successful in his or her chosen occupation and benefit him or herself, the workforce, the community, and the economy (Moreland, 2006). While many countries draw attention to the connection between employability skills and the program of study in higher education, there are still conflicts involved in reintroducing vocationalism into higher education. Bourner, Greener, & Rospigliosi (2011) advocates a new vocationalism approach to new graduates' employability. The purpose of new vocationalism in higher education is to orient programs towards developing students' willingness and ability to learn and be active members of society afterwards. The goal is to enhance students' powers of learning in order to increase their career prospects. The learning focuses on the acquisition of new and needed knowledge and skills for employment after graduation. The benefit of practicing new vocationalism is to build on the existing values of higher education and produce students who are better prepared to learn job skills than non-graduates (Bourner, Greener, & Rospigliosi, 2011).

Theoretical Model

According to the Quality Assurance Agency (QAA) for Higher Education Code of Practice (2001), it suggests that decision, opportunities, transitions, and self (DOTS) model has been considered a good practice approach and been a widely adopted strategy for preparing students' career learning in higher education (Watts, 1977). The key features of DOTS model were integrated employability and enterprise skills into the degree curriculum. Specially, DOTS model promotes students' (1) self-awareness (i.e. motivations, skills, and personality influence on career plans, (2) opportunity awareness (i.e. knowledge of and ability to research opportunities, (3) decision making (i.e. assessing personal factors to make decision, and (4) transition learning (i.e. how to seek and secure opportunities). Based on the DOTS model, Rae's career development model (2007) is to apply DOTS model at a practical level.

Originally, Rae's career development theory was designed for educators for curriculum design in business higher education in the United Kingdom. The theory suggests that business higher education should integrate career service, enterprise, and graduate employability into the degree curriculum (Rae, 2007). The model is consisted of five strand approaches (i.e., personal development, applied learning, skill development, work-based learning, and career management) which provide guidelines for integrating career learning opportunities into degree programs. The theoretical model is presented below in Figure 1.

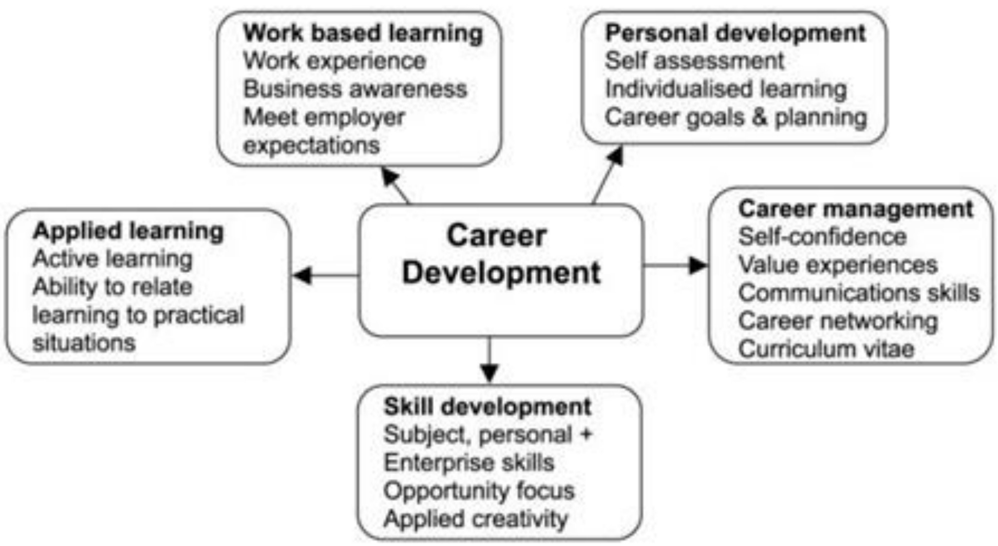


Figure 1. The career development model. Adapted from "Connecting Enterprise and Graduate Employability: Challenges to the Higher Education culture and Curriculum?" by Rae, D., 2007, *Education+ Training*, *49*(8/9), p. 616.

Personal Development

In previous studies, there are many theories indicating the importance of personal development or management related to an individual's career decisions (Parsons, 1909; Supper, 1990). The career and employability skill (C&ES) model describes personal management skills as students' abilities to display personal qualities such as responsibility, self-management, ethical behavior, and respect for both self and others (Zinser, 2003). Parsons also states that one of the best ways to choose a vocation is to have a clear understanding of ourselves, including our aptitudes, interests, ambitions, resources, knowledge, and limitations (Parsons, 1909). According to Supper (1990), the definition of career is the integration and sequence of roles which a person undertakes during his or her life time. The "Life Career Rainbow" presents the mean of an individual's career development throughout his or her life. An individual's career decision is modified by the interactions between a variety of personal and situational determinants. Specifically, personal management and development consists of understanding personality traits, interests, attitudes, values, needs, academic achievement, and self-awareness how they influence individual career decision making (Supper, 1990). Often, a university's student success center offers the career services to support students' personal development in a unified higher education system (Kyvik, 2004). Researchers created personal development planning in order to better prepare first year undergraduate students for future career development. The results found that undertaking personal development planning could benefit students' career retention, clarify career goals, and increase motivation toward their chosen majors (Monks, Conway, & Dhuigneain, 2006).

Rae's personal development focused on encouraging students to attend courses or training offered by professional development systems to support the personal development process, empowering the students' ability to set personal goals for individualized learning. Constantly self-assessing and reflecting on learning and skill gains, as well as retaining the evidence of learning and attainment, and applying these to produce useful documents such as career plans, curriculum vitae, and job applications are necessary for career management later on (Rae, 2007).

Applied Learning

Applied or transfer learning skill is the way students apply basic reading, writing, speaking, listening, subject knowledge and skills in work-related situations (Zinser, 2003). Researchers found that there are three types of transfer learning that occur: (a) from prior knowledge and skills to new learning, (b) from new knowledge and skills to new learning situations, and (c) from new knowledge and skills to applications in work and daily life. Simons (1990; 1999) suggested that promoting transfer learning is better if initiated from the learner's perspective, and students should be encouraged to use prior knowledge actively and shown how to do this on their own. Ford's transfer training model (1997) demonstrates how learners' characteristics, instructional design, and environment influence their retention level and whether transfer learning occurs. Applied learning also includes students' ability to identify, organize, plan, and allocate resources such as time, money, materials, and human resources (Parsons, 1909; Zinser, 2003). Parsons believed that students should have knowledge of the requirements and conditions of success, advantages and disadvantages, compensation, opportunities, and prospects in different lines of work. Every young person needs help with these three points of transfer learning in order to receive information and assistance. Careful and systematic guidance could provide support for students' career decisions (Parsons, 1909).

The concept of applied learning from Rae's study (2007) suggested degree programs should connect theoretical, cognitive, and subject-based learning to help students apply this knowledge in practice to increase their ability to transfer skills between university and the workplace in the future. Applied learning opportunities within a degree include (a) work-based projects and assignments, (b) problem, opportunity and activity-based learning, (c) study visits to employers and external organizations, (d) guest speakers from industry and live case studies, and (e) interactive and simulation-based learning. The main differences between work-based learning and applied learning is that applied learning goes beyond the focus of work-based learning; it requires critical reflection, assignments, and reports to show evidence that students' applied and transfer learning occurred (Rae, 2007).

Skill Development

Based on teachers', education experts', and business leaders' perspectives, the P21-framework defines and illustrates the skills and knowledge students need to succeed at work (Greenhill, 2009). All 21st century skills and knowledge are divided into five domains: key subjects, learning and innovation skills, information-media-technology skills, life and career skills, and social-cross-cultural skills. First, the key subjects for all students in the 21st century include English, reading or language arts, word languages, arts, mathematics, economics, science, geography, history, government and civics. In addition, teachers and experts believe that schools also need to provide 21st century interdisciplinary themes in key subjects such as global awareness, finance, economics, business and entrepreneurial literacy, civic literacy, health literacy, and environmental literacy. Second, learning and innovation skills focus on creativity, critical thinking, communication, and collaboration skills in order to prepare students to face more and more complex life and work environments in the 21st century. Third, information, media and technology skills develop students' ability to access, manage, and utilize an abundance of information, as well as rapid changes in technology tools. Fourth, life and career skills help students to develop the ability to navigate and adapt to complex life and work environments. It also requires students to manage their goals and time, and explore their own learning opportunities in order to gain expertise. Finally, social and cross-cultural skills prepare students to interact effectively with others and work effectively as part of a diverse team (Greenhill, 2009).

In a STEM report from the Center on Education and the Workforce at Georgetown University, researchers generalized a list of core skills and abilities required for students and employees to succeed in all STEM occupations. There are five different domains included in this model: abilities, skills, knowledge, interests, and values (Table 1). Researchers listed skills specifically required in each domain (see Table 1), and they found that in 95 percent of STEM occupations, mathematics skill is considered important for fulfilling the requirements of that occupation (Carnevale, Smith, & Melton, 2011). The importance level of students' mathematics and science skills significantly impacts economic growth. A recent study conducted by Hanushek, Peterson, and Woessmann (2012), a senior fellow at the Hoover Institution at Stanford University, shows that one standard deviation difference in mathematics and science scores may relate to a one percent difference in annual per capital gross domestic product (GPD) growth rates (NCEE, 2008; Carnevale, Smith, & Melton, 2011). In addition, critical thinking is another skill requirement in STEM fields. Ninety-six STEM occupations and 92 STEM competitor jobs consider critical skills to be either very important or extremely important to STEM jobs. Science skills are either important or extremely important for more than half of the available STEM occupations. Carnevale's report also lists abilities required in all STEM occupations, which includes problem sensitivity, deductive reasoning, inductive reasoning, mathematical reasoning, number facility, perceptual speed, and control precision. Researchers believe that STEM abilities are even more transferable than STEM knowledge (Carnevale, Smith, & Melton, 2011).

Table 1

A Brief List of STEM Competencies

STEM Competencies				
Knowledge	**Skills**	**Abilities**	**Work Values**	**Work interest**
Mathematics, Chemistry, Biology, Engineering, Technology, English Language, Economics, Accounting, Clerical Food production	Content skill, Processing skill, Problem-solving skill	Creativity, Innovation, Mathematical reasoning, Oral and Written expression	Recognition, achievement, working conditions, security, advancement, authority, social status, responsibility, compensation	Individual preferences for working environment, Particular interests such as realistic, artistic, investigative, social, enterprising, conventional

Note, Adapted from "STEM: Science Technology Engineering Mathematics," by Carnevale, A. P., Smith, N., &Melton, M., 2011, *Georgetown University Center on Education and the Workforce*.

The state of Michigan also published a set of curriculum standards and benchmarks for career and employability skill (C&ES). This report describes three areas of skills that employers require: academic, personal management, and teamwork skills (Zinser, 2003). In the following years, the C&ES model provided more comprehensive curriculum standards and was approved by the Board of Education to help high school students move successfully into the world of work or continuing education and achieve their career goals. Researchers summarized ten career and employability skill standards, including personal management, applied academic skills, organizational skills, teamwork, problem solving, understanding systems, using employability skills, career planning, developing and presenting information, and negotiation skills (Michigan Department of Education, 1998; Zinser, 2003). To meet the requirement for skill development, the career development theory (Rae, 2007) suggests that the program study and courses should offer personal skills, social skills, and task skills to help students develop both subject specific and generic skills. More importantly, these skills will integrate with their degrees, and each degree will have its own range of specific skills that students are required to develop (Rae, 2007).

Work-based Learning

Work-based learning becomes an essential tool for increasing students' personal development, applied learning, and skill development for them to succeed in the workforce. Specifically, work-based learning could enhance students' development as self-managing practitioners, and self-directed learning aligns with the needs of workforce and facilitates personal growth and development (Rae, 2007). In the last two decades, there has been an expansion of universities offering classes that involve work-based learning, to allow students to apply academic knowledge and skills in a real working environment. Researchers found that a set of principles and practices can lay out work-based learning within universities more efficiently than within professional fields. Students' ability to apply what they learn in immediately practical work is a catalyst for personal growth (Lester & Costley, 2010).

According to Gomez, Lush, and Clements's study (2004, students having work-based learning experiences could enhance their academic performance. Researchers found that bioscience placement students (n=164) gain an advantage of nearly 4% in their final year performance after work-based learning experiences (Gomez, Lush, & Clements, 2004). The National Council for Work Experience in the UK proposes that "work experience greatly improved students' understanding of subject knowledge and skills" (Mandilaras, 2004; Gomez, Lush, & Clements, 2004). Possible explanations of the improvement include (a) a competitive professional environment in the work placement will promote students' maturation rapidly, (b) students' ambition will be stimulated, which will increase their engagement and determination after they return to university, and (c) workplace responsibilities may enhance students' reliability, cause them to take coursework and exams more seriously, and make them study more effectively. Overall, the work placements could increase students' academic performance (Gomez, Lush, & Clements, 2004; Mandilaras, 2004).

However, the efficiencies of work placements are still influenced by many factors. First, the work placement must have a direct link to academic performance. For instance, bioscience work placements require work in a laboratory which is likely to benefit students doing their research projects in their final year, particularly if the work placement and research project are related. Therefore, a work placement is more likely to transfer more generic skills such as team-work, communication, self-reliance and confidence, time management, etc. Second, work placement supervisors may make significant contributions to students' academic performance. Specifically, the supervisors are aware of how the work placement is linked to the subsequent academic study, and could subsequently cause the placement to be more valuable (Duiguan, 2002; Mandilaras, 2004; Gomez, Lush, & Clements, 2004). Finally, students' attitudes toward their work experiences will influence the degree to which the work benefits their academic performance. Researchers found that using the work placement as an addition to the core program of study is more beneficial to student academic performance rather than incorporating it as an integral part of the program of study (Gomez, Lush, & Clements, 2004).

Rae's career development theory suggested that work-based learning is an essential aspect of every degree, as it provides opportunities for personal development, applied learning, and skill development (Rae, 2007). The results of experiencing and assessing the outcomes from work-based learning could not only help students to learn the subjects within their degree, but also help them to understand the features of work and a typical work environment. As one research study suggests, the STEM worker supply is strongly influenced by earnings, job security, and working conditions (Carnevale, Smith, & Melton, 2011). Work-based learning provides opportunities for students to make better career decisions. There are many types of work-based learning, such as internships, cooperative learning experiences, short-term work experiences, a full academic year of work placement experiences, relevant part-time works, volunteer, community and social work activities, and organization of student clubs (Rae, 2007).

Career Management

The career management concept suggests that students should participate in ongoing career development activities to improve career management. This skill plays the role of integrating all four of the other employability skills to achieve students' career development. There are some specific career education activities and training that can be used to promote students' career management skills, including job searching, application writing, interview preparation, self-presentation and communications skills, individual career guidance, and professional career networks. Those activities could be made specific to STEM subjects and vocations or wide industry and generic career guidance (Rae, 2007).

In the current study, researchers developed a career development assessment based on Rae's study for assessing students' career development in STEM higher education fields. Rae's study presents 40 principles to describe the detail of career development experiences that should integrate into curriculum design in each domain (see Table 2). Based on these principles, researchers developed a 58 questionnaire for assessing students' career development in STEM higher education.

Table 2

Guidelines for Developing Career Development Assessment

Career Development Domain	NO.	Detail of Career Development
Personal Development (PD)	1	Enabling to set goals for personal learning.
	2	Self-assessing and reflecting on learning and skills for gaining ownership and retain evidence of personal learning and skills.
	3	Producing useful documents (i.e., resume, curriculum vitae or job application) to meet employer acceptance criteria and development of a career plan according to (2).
Applied Learning (AL)	4	Making connections between theoretical, cognitive, and subject-based learning, and to apply this knowledge in practice and to transfer skills between university and the workplace.
	5	Through work-based projects and assignments to show evidence of the applied learning and transferring skills from academia to workforce.
	6	Visiting employers and organizations related to the degree programs.
	7	Guest speakers from industry.
	8	Live case studies and projects (opportunities to get some hands-on experience applying theories and models to real firms).
	9	Interactive and simulation based learning (mimicking working environment).
Skill Development (SD)	10	Personal organization and time management.
	11	Self-confidence and self-efficacy.
	12	Personal budgeting and financial literacy.
	13	Finding opportunities and taking the initiative to act on opportunities.
	14	Creative thinking and problem solving.
	15	Making decisions and accepting risks in conditions of uncertainty.
	16	Planning, setting goals and persevering to achieve goals.
	17	Working independently and taking responsibility for achieving results
	18	Project management skills.

Note: Adapted from Rae's 40 Principles of Career Development Experiences in Curriculum Design (2007).

Table 2

Guidelines for Developing Career Development Assessment (continued)

Career Development Domain	NO.	Detail of Career Development
Skill Development (SD)	19	Self-presentation and a range of verbal and written communications skills.
	20	Interpersonal skills of relationship building, negotiation, persuasion and influencing.
	21	Leadership skills in a range of situations.
	22	Team working effectively to achieve results with others.
	23	Participating in social and industry or professional networks.
	24	Computer literacy and its skills.
	25	Numerical, analytical, and quantitative skills.
	26	Applying academic learning in practical settings including the workplace.
	27	Adapting and work flexibly in different contexts.
	28	Taking responsibility for completing work to quality standards.
Work-Based Learning(WB)	29	Short-term work experience placement of 6-12 weeks.
	30	A full academic year work experience placement.
	31	Relevant part-time, casual or vacation work.
	32	Self-employment or freelancing.
	33	Voluntary, community, or social enterprise work activity.
	34	Leadership or organization of student clubs, sports activities, or societies.
Career management(CM)	35	Training on resume (curriculum vitae) preparation.
	36	Job searching.
	37	Self-presentation and communications skills to develop self-confidence.
	38	Individual careers guidance.
	39	Access to industry, vocational or professional practitioner input.
	40	Access to career preparation in university, industry, professional careers events, and networks

Note: Adapted from Rae's 40 Principles of Career Development Experiences in Curriculum Design (2007).

CHAPTER III

METHOGOLOGY

This section is structured in the following manner: research design and rationale, a description of the participants of this study, followed by a description of the research variables and instruments used in the procedures, the methods of data gathering, and data analyses. A brief overview of the hypotheses proposed is provided, followed by a description of the statistical analysis methods used, along with a summary.

Participants

This study included two stages. In the first stage, it developed a career survey for assessing students' career development in STEM higher education. It involved 109 senior-year students who enrolled in STEM education in spring 2017 and 35 young new STEM graduates who graduated in spring 2016. The steps of recruiting participants are shown in Table 5. The responded rate of senior-year students was 24.82%. The recruitment of new graduates all came from emails which they gave to the alumni association at a university in southeast Virginia during the spring 2017. There were a total 287 new STEM graduates who fit our requirements in spring 2016. After sending them an email, there was a 34% open rate and a 13.59 % response rate for spring 2016 new graduates. STEM majors which were recruited from Aerospace Engineering, Biochemistry, Biology, Chemistry, Civil Engineering, Computer Engineering, Computer Science, Electrical Engineering, Electrical & Computer Engineering, Engineering Management, Engineering Technology, Mathematics, Mechanical Engineering, Modeling & Simulation Engineering, Ocean and Earth Science, Physics, and Systems Engineering majors. The average age of the sample in this study was 23.08 years old (SD = 1.76). Each participant received extra credit for his or her participation, and alternative ways of earning such credit were also available for those who did not participate in the study.

Instruments

The survey was comprised of a demographic questionnaire, career development assessment, career barriers inventory (new graduates only), and employment status (new graduates only). They were all measured on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). Students' demographic questionnaire was included gender, age, ethnicity, major, and GPA etc. Researchers listed all variables by hypotheses in Table 3.

Demographic Questionnaire

Demographic questionnaire items included gender, age, ethnicity, major, experiences of taking CTE, utilizing career service, GPA etc.

Career development assessment (employability)

Based on Rae's 40 principles (see Table 2), researchers developed a 58 item career development assessment in five domains including (a) personal development (e.g., my major gave me support and encouragement that enabled me to set goals for my personal learning), (b) applied learning (e.g., my major gave me support and encouragement that enabled me to make connections between theoretical, cognitive, and subject-based learning), (c) skill development (e.g., major helped me to obtain the skill of creative thinking), (d) work-based learning (e.g., my major provided me with a short-term work experience placement of 6-12 weeks), and (e) career management (e.g., my major provided me training on job searching). Respondents indicated their satisfaction on a Likert-type scale of 1 (strongly disagree) to 5 (strongly agree).

Employment Status

Employment status is a single item asking new graduates to report their current employment status. The responses were included: “I am a full-time employee working 40 hours per week and the job is related to your major”, “I am a part-time employee working less than 40 hours per week and the job is directly related to your major”, “I am a full-time employee working 40 hours per week and the job is not related to your major”, “I am a part-time employee working less than 40 hours per week and the job is not related to your major”, and “I am still looking for jobs”.

Career Barriers Inventory

Career Barriers Inventory Revised (CBI-R; Swason, Daniels & Tokar, 1996) originally is a 70-item measure to assess graduates’ career barriers. It is divided into 13 subscales including sex discrimination, lack of confidence, multiple role conflict, conflict between children and career demands, racial discrimination, inadequate preparation, disapproval by significant, decision-making difficulties, dissatisfaction with career, discouraged form choosing nontraditional career, disability/health concerns, job market constraints, and difficulties with networking or socialization. In the present study, researchers only emphasized on 6 subscales including (a) lack of confidence (e.g., not feeling confident about myself in general), (b) inadequate preparation (e.g., lacking the required skills for my job), (c) decision-making difficulties (e.g., changing my mind again and again about my career plans), (d) dissatisfaction with career (e.g., being dissatisfied with my career), (e) job market constraints(e.g., difficulty in finding a job due to a tight job market), and (f) difficulties with networking or socialization(e.g., not knowing the right people to get ahead in my career). Each item is reported on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), and they were only used to assess new STEM graduates in current study. Researchers summarized all variables corresponding to each hypothesis (see Table 3).

Table 3

Research Variables for Hypothesis

NO.	Variable	IV/DV	Data Type
H 1	Personal Development	IV	Interval
	Applied Learning	IV	Interval
	Skill Development	IV	Interval
	Work-based Learning	IV	Interval
	Career Management	IV	Interval
H 2	Career Technical Education	IV	Dichotomous
	Career Service	IV	Dichotomous
	Career Development (revised)	DVs	Interval
H 3	STEM Majors	IV	Ordinal (4 levels)
	Career Development (revised)	DVs	Interval
H 4	Employment Status	IV	Dichotomous
	Career Development (revised)	DVs	Interval
H 5	Employment Status	IV	Dichotomous
	Career Barriers (six variables)	DVs	Interval
H 6	Career Development (revised)	IVs	Interval
	Employment Status	DV	Dichotomous
H 7	Career Development (revised)	IVs	Interval
	GPA	DV	Interval

Research Design and Rationale

Cross-sectional study was chosen to answer the research questions as well as test the hypotheses. Furthermore, they were used to test internal and external reliability of assessment and models which were created in the current study. Although using the cross-sectional study could not confirm the causality, it could generate useful data for possibly using experimental design (Levin, 2006).

Procedures

The primary source of data was an online survey. Interested participants were contacted via an e-mail, in which they were given a sheet explaining the purpose and details of the study, along with a link to the survey. Prior to the beginning of the survey, an informed consent script articulating the study purposes, risks, and benefits was provided. Participants were required to give written consent acknowledging their agreement to participate in the study before they began answering the survey questions. Participants took approximately 30 minutes to answer all survey questions for each stage, and the data collection process was completed during the fall 2016 and spring 2017 (see Table 4).

Table 4

Cross-sectional Study Data Collection Processes

Data Source		
Spring 2017 Cross-sectional Data	Participants A (Senior Students)	
	Assessments	1. Demographic 2. Career Development
Spring 2017 Cross-sectional Data	Assessments	1. Demographic 2. Career Development 3. Career Barriers 4. Employment Status

Data collected during this study was used to measure current students' career development, new graduates' career barriers, and their employment status. This study relied on assumptions about the variables used in the analysis. Exploratory factor analysis was used to test the first hypothesis, multivariate analysis of variance **(**MANOVA) to test hypotheses 2-5, logistic regression to test hypothesis 6, and generalized linear model (GLM) to test hypotheses 7 and 8. In addition, researchers also performed normality test, power analysis, reliability testing, multicollinearity diagnostics, and models' internal validations for supporting the results from testing the hypotheses. The details of data analyses with hypotheses were shown in Table 5. After data collected, they were inputted into both SPPS and SAS which were the software of choice for the analysis of the obtained data. Researchers divided the data analyses into four sections based on the types of data analyses. In the current study, there were four types including (1) data analysis one: exploratory factor analysis, (2) data analysis two: multivariate analysis of variance, (3) data analysis three: logistic regression analysis, (4) data analysis four: generalized linear model analysis, and (5) data analysis five: Markov Chain Monte Carlo (MCMC) model validations.

Table 5

Details of Data Analyses by Hypotheses

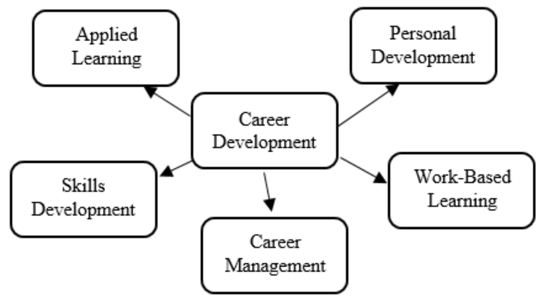
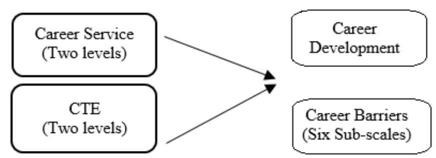
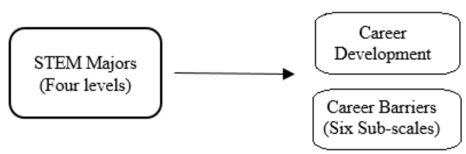
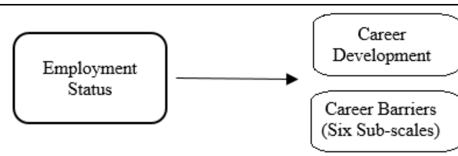
No.	Hypothesis	Diagram	Data Analysis
1.	Student's career development consists of five factors including personal development, applied learning, skill development, work-based learning, and career management.		1. Variables Normality Test 2. Power Analysis 3. Exploratory Factor Analysis
2.	Students that utilized career services and took CTE courses have higher levels of career development and lower levels of career barriers.		1. Multivariate Analysis of Variance (MANOVA) 2. Box's M Test
3.	Students with different STEM majors have different levels of career development and career barriers.		1. MANOVA 2. Box's M Test
4.	Individuals employed full-time in STEM have higher levels of career development and lower levels of career barriers.		1. MANOVA 2. Box's M Test

Table 5

Details of Data Analyses by Hypotheses (continued)

No.	Hypothesis	Diagram	Data Analysis
5.	Student's career development in STEM higher education will predict their career barriers in STEM workforce.	Employment Status → Career Barriers (Six Sub-scales)	1. MANOVA 2. Box's M Test
6.	Student's career development in STEM higher education will predict their employment status.	Career Development → Employment Status	1. Logistical Regression 2. Using Markov Chain Monte Carlo (MCMC) Validation
7.	Student's career development in STEM higher education will predict their GPA	Career Development → GPA (Control gender and majors)	1. Generalized Linear Model **(**GLM) 2. Power Analysis 3. Multicollinearity Diagnostic 4. MCMC Validation

Exploratory Factor Analysis

The goal of data analysis one was to develop the career development assessment based on Rae's theoretical model (2007). In this step, researchers performed normality testing and power analysis before running exploratory facto analysis.

Testing Distributions for Normality

Normality testing is an important analysis in quantitative and inferential statistical analyses because conclusions are not correct if data are not normally distributed. In the current study, researchers chose Skewness and Kurtosis to test the distribution's symmetry and Shapiro-Wilk to test the distribution's normality of each data set were collected.

Skewness and Kurtosis

Skewness is a data analysis to test the probability and value of a random variable distribution is an asymmetry. The skewness for a normal distribution is zero. The negative skew represents the tail on the left side of probability density is longer than the right side of probability density, and the positive skew is the opposite of the negative skew. The kurtosis is a data analysis to test the tailedness of the probability distribution. The kurtosis for a normal distribution is 3.0 (excess kurtosis exactly 0) which is called mesokurtic. A distribution of kurtosis is less than 3 (excess kurtosis < 0), it is called platykurtic. On the other hand, it is said to be leptokurtic 3 (excess kurtosis >0 which the kurtosis is greater than 3 (Warner, 2008).

The probability theory of Skewness and Kurtosis were analyzed using the following formulas:

$$Skewness = \frac{\sum(yi - y)^3}{(n-1)^3}$$

$$Kurtosis = \frac{\sum(yi - y)^4}{(n-1)s^4}$$

where

y = the mean of a random variable

yi = the raw score of observation i

n = the total number of observation

s = the standard deviation

Shapiro-Wilk

Meanwhile, Shapiro-Wilk normality test was used to determine the data whether normally distributed because Shapiro–Wilk has the best power for a given significance according to Monte Carlo simulation (Razali & Wah, 2011). The null hypothesis of Shapiro-Wilk is that the sample is normally distributed (Shapiro & Wilk, 1965). The equation of the Shapiro-Wilk calculation used:

$$W = \frac{(\sum_{i=1}^{n} a_i x_i)^2}{(\sum_{i=1}^{n} x_i - \mathrm{x})^2}$$

where

$x_i =$ $the\ score\ of\ item\ "i"$

$x =$ $(x_1 + x_2 + \cdots + x_n)/n$

$a_i =$ The constants $a_i = \frac{m^T V^{-1}}{(m^T V^{-1} V^{-1} m)^{1/2}}$

m = $(m_1, m_2, \ldots. m_n)^T$. Expected values of the order statistics of independent and identically distributed random variables sampled from the standard normal distribution.

V = covariance matrix of those order statistics

In the real-world setting, the normal distribution is unrealistic. In the current study, the acceptable limits of the skewness and kurtosis are ±1.96 (Trochim & Donnelly, 2006; Field, 2000 & 2009; Gravetter & Wallnau, 2014).

Power Analysis and Sample Size Test

The purpose of power analysis was to optimize the design of the study and the efficiency of conclusive results which could improve the chances of detecting a true effect, save time, money, and minimize risks to subjects (SAS®, 2008). A substantial sample size could also increase the power of external validation (Steyerberg, Bleeker, Moll, Grobbee, & Moons, 2003). There are many criteria that are used to determine the sample size based on the power analysis in factor analysis. Guilford (1954) suggests that sample size should be at least 200 for factor analysis. Comrey and Lee (1992) provided a brief rating scale for evaluating the sample size of confirmatory factor analysis: 100 = poor, 200 =fair, 300=good, 500=very good, and 1000 or more as excellent (Comrey & Lee, 1992; Williams, & Brown, 2010). Floyd and Widaman also suggested that he minimal number of samples should be 10 times the numbers of variables being analyzed (Floyd & Widaman, 1995; Osborne, & Costello, 2009; O'Rourke & Hatcher, 2013). Although EFA requires a relatively bigger sample size, researchers suggest that if correlation coefficients >.80, fifty sample cases may be efficient for factor analysis (Guadagnoli & Velicer, 1988; Sapnas & Zeller, 2002). Finally, using the Monte Carlo method to decide on sample size, the parameter and standard error biases could not exceed 10% for any parameters in the simulations. In addition, the standard error bias of the power is not to exceed 5%, and confidence interval coverage remains between 0.91 and 0.98. Once these three criteria are satisfied, the sample size will keep the power close to 0.8 which is a well-accepted value for large enough power (Muthén & Muthén, 2002).

Exploratory Factor Analysis

In general, there are five objectives of performing exploratory factor analysis (EFA) including to (1) reduce the number of variables, (2) examine the relationship between variables,

(3) evaluate validate of assessment, (4) test multicollinearity, and (5) test/prove/modify a theoretical model. EFA was used to reduce the dimensionality of the theoretical model to a reduced number of new dimensions. Based on a Rae's career development theoretical model, exploratory factor analysis is used to identify the underlying component factors between latent constructs and measured variables. Through appropriately evaluating and selecting factor analysis, correlation matrices, factor extraction, choosing the number of factors to retain, factor rotation, component score coefficient matrix, and factor interpretation (Spriggs 2017).

In current study, EFA was used to test the first hypothesis whether all 58 items intercorrelated and underlined personal development, applied learning, skill development, work-based learning, and career management domains/factors. Each observed item was divided into common and unique components in exploratory factor analysis. In other words, EFA was used to estimate factors that influence responses on observed variables including common factors model and unique factor model (Figure 2). Researchers used convergent and discriminant validity to estimate common and unique components in exploratory factor analysis, and they are both subcategories of construct validity for making sure the items of a measurement work together (Suhr, 2005).

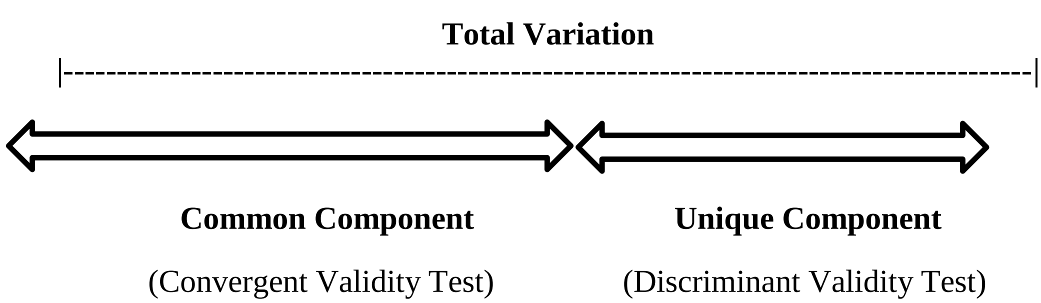


Figure 2. Common component and unique component in a variable. Adapted from "A Step-by-step Approach to Using SAS for Factor Analysis and Structural Equation Modeling" by O'Rourke, N. and Hatcher, L., 2013. SAS Institute.

Convergent Validity

The function of convergent validity is to test whether the constructs (factors) are related. The first step was to check items correlation matrices for making sure the items of constructs were highly correlated. Many ways can assess convergent validity. In the current study, researchers chose Kaiswer-Meryer-Olkin's (KMO), Bartlett's Tests, *individual* items' reliability (standard ≥ 0.5), composite construct reliability (similar to Cronbach's alpha-standard ≥ 0.7), and average variance extracted (AVE; standard ≥ 0.5) to test convergent validity (Fornell and Larcker 1981; Spriggs 2017).

KMO and Bartlett's Tests

The first method of testing convergent validates was using Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy. KMO was able a measure of sampling adequacy (MSA) for each item and overall variables. KMO index could tell researchers the fitness of performing factor analysis using a dataset. It ranges from 0 to 1. $KMO <.5$ indicates that model does not fit; $0.5<KMO<0.6$ poorly fit; $0.6<KMO<0.7$ is suitable; $0.8<KMO<0.9$ fit; $KMO> 0.9$ is very suitable to perform factor analysis (Cerny & Kaiser, 1977). Bartlett's Test is to test whether the correlation matrix is identical; wherefore, the null hypothesis of Bartlett's Test of Sphericity is identity matrix. If the correlation matrix is identical, factor analysis cannot be performed. In other words, Bartlett's Test of Sphericity should be significant ($p<.05$) to reject the null hypothesis which was eligible to perform factor analysis.

Reliability Test

In the current study, researchers were following the steps of EFA protocol to perform EFA analysis (Rietveld & Van Hout, 1993; Williams, Brown, Onsman, 2010). In the first step, Cronbach's alpha was used to test the reliability of measurement, specifically using coefficient alpha to test internal consistency. While developing an assessment, Cronbach's alpha is a prerequisite of determining to keep or remove the scales from an assessment. The internal reliability is positively correlated with correlations between items. In other words, high correlations between items will increase internal reliability (Spriggs, 2017). The formula for testing scale reliability was based on internal consistency which provides the lowest estimate of reliability of an instrument. The higher coefficient alpha represents a strongly correlated instrument. In other words, the instrument has higher reliability. Usually Cronbach's alpha is required to be more than .7 for it to be considered a reliable scale (O'Rourke & Hatcher, 2013).

$$r_{xx} = (\frac{N}{N-1})(\frac{(S^2 - \sum S_i^2)}{S^2}$$

where

r_{xx} = coefficient alpha

N = number of items constituting the instrument

S^2 = variance of the summated scale scores (e.g., assume that you compute a total score for each participant by summing responses to the items that constitute the scale; the variance of this total score variable would be S^2)

$\sum S_i^2$= the sum of the variances of the individual item i that constitute this scale

Factor Dimensionality

The second step was to determine how many factors to be retained through performing extraction in EFA. In the current study, researchers were trying to get the minimum number of items with the maximum total variance. Based on this goal, it was analyzed via principal components analysis (PCA). There are some rules of thumb for determining how many factors should be retained including (1) factors with an eigenvalue larger than 1 (Guttman-Kaiser rule), (2) factors which in total account for about 70-80 % of the variance, (3) factors before the breaking point of elbow based on the scree-plot (Field 2000, Rietveld & Van Hout, 1993), and (4) each factor should have at least three observed measurement/items (O'Rourke & Hatcher, 2013).

Communality

The initial communality of each observed variable is 1. After performing factor extraction for testing convergent validity, the communality of each observed (h^2) variable computed by the sum of squared factor loading. In other words, communalities are the proportion of each variables' variance explained by the factors (O'Rourke & Hatcher, 2013). Fornell and Larcker (1981) suggested that the average variance extracted (AVE) should be above .5 which is an indicator whether the variance construct exceeds the measurement error. The equation of computing communality and AVE are as follow:

$$h_1^2 = \beta_{11}^2 + \beta_{21}^2 + \cdots + \beta_{n1}^2$$

$$h_2^2 = \beta_{21}^2 + \beta_{22}^2 + \cdots + \beta_{n2}^2$$

$$\vdots$$

$$h_m^2 = \beta_{m1}^2 + \beta_{m2}^2 + \cdots + \beta_{nm}^2$$

$$AVE = (h_1^2 + h_2^2 + \cdots + h_m^2)/\mathrm{m}$$

where

h_1^2 = the communality for 1st observed variable

m = the number of observable variable

β_{11}^2 = the first observed variable 's regression weight for factor 1

n = the number of factor

AVE = the average variance extracted

Discriminant Validity

Unlike convergent validity to test whether the constructs are retaliated, the function of discriminant validity is to test if the constructs have not relationship. Researchers suggest that discriminant validly exists if constructs have higher loadings in its own block than other blocks which is relied on rotation to test discriminant validity (Chin, 1998; Spriggs, 2017).

Rotation

A factor analysis was used to determine if the items for the scales had discriminant validity through performing rotation. In general, there are two types of rotations including orthogonal methods (i.e. equamax, orthomax, quartimax, and varimax) and oblique methods (i.e. oblimin and promax). The orthogonal methods assume that there are no correlations among factors; on the other hand, the oblique methods assume that factors are correlated (Osborne & Costello, 2009). Discriminant validity (or divergent validity) exists if constructs/factors that should have no relationship in fact are un-related (Chin 1998). In the current study, researchers chose orthogonal rotations.

Factor Score Computation

There are many ways to computer the factor score. There are two main classes of factor score computation methods: non-refined and refine. Non-refined methods are simple to use and easy to interpret. The most frequently used for the non-refined methods include (1) sum scores by factor, (2) sum scores above a cut-off value, (3) sum scores of standardized variables, (4) weighted sum scores. Refined methods, on the other hand, are more sophisticated and technical approaches, and they are often applied when principal components and common factor extraction methods are used in EFA. The most common refined methods were used standardized information to create factor scores. The standardized scores similar to a Z-score metric ranges from -3.0 to + 3.0. They are included (1) Thurston's regression scores, Barlett scores, and Anderson-Rubin scores (DiStefano, Zhu, Mindrila, 2009). The differentiations of computing factor score were shown in Table 6 and Table 7. Each variable can be also explained by the factors. In the following equations were represented each observed variable as being a weighted sum of the underlying factors.

$$x_1 = \beta_{11}F_1 + \beta_{21}F_2 + \cdots \beta_{n1}F_n + \varepsilon_1$$

$$x_2 = \beta_{12}F_2 + \beta_{22}F_2 + \cdots \beta_{n2}F_n + \varepsilon_2$$

$$\vdots$$

$$x_m = \beta_{1m}F_1 + \beta_{2m}F_2 + \cdots \beta_{nm}F_n + \varepsilon_m$$

where

X_m = the participant's score on observed variable m

β_{nm} = the regression coefficient (or weight) for underlying common factor n, as used in determining the participant's score on X_m

F_n = the participant's n factor score

ε_m = the error variance of X_m

Table 6

Non-Refined Methods to Compute Factor Scores

Method	Procedure	Advantages	Considerations
Sum Scores by Factor	Sum raw scores corresponding to all items loading on the factor. (Items with negative loadings Are subtracted in the score creation.)	In the metric of what is studied. Can be averaged to reflect the scale of the items. Easy to calculate and interpret. If factor scores are used in later analyses, sum scores preserve variation in the data.	Gives items equal weight when the weight of item to factor (loading values) may be very different.
Sum Scores Above a Cut-off Value	Sometimes a cutoff loading value is used and items above the cutoff are summed.		Cutoff is arbitrary. A higher cutoff may result in including fewer variables used, a lower cutoff will include variables with a weaker relationship to the factor.
Sum Scores - Standardized Variables	Scale raw scores to same mean and standard deviation before summing. Can apply a cutoff loading value and only add items above the cutoff.	Useful to deal with observed variables that vary widely in terms of standard deviation units. Refinement worth effort unless observed variables are reasonably similar in the size of standard deviations.	If standard deviations of raw scores are similar, sum scores without standardizing are easier to compute. No weighting given to items with higher loadings.
Weighted Sum Scores	Take into consideration the loading values in the factor score creation. Multiply the factor loading to the scale score then sum. Can be applied to items above a certain loading value or all items on a factor.	Recognizes the strength (or lack of strength) for items. Items with highest loadings have the most effect on the factor scores.	Possibility that differences in factor loadings are due to EFA extraction and rotation choices. If differences are due to EFA procedures, this method may not be better than creating summed scale scores.

Note. Adopted from “Understanding and Using Factor Scores: Considerations for the Applied Researcher,” by DiStefano, C., Zhu, M., & Mindrila, D., 2009, *Practical Assessment, Research & Evaluation*, *14*(20), p.8.

Table 7

Refined Methods to Compute Factor Scores

Method	Procedure	Advantages	Considerations
Regression Scores	Multiple regression used to estimate (predict) factor scores. Default procedure to compute factor scores in SAS and SPSS packages; also available in R.	Factor scores are standard scores with a Mean =0, Variance = squared multiple correlation (SMC) between items and factor. Procedure maximizes validity of estimates.	Factor scores are neither univocal nor unbiased. The scores may be correlated even when factors are orthogonal
Bartlett	Method of producing factor scores is similar to regression method, but produces estimates that are most likely to represent the true factor scores. Can be computed using SPSS or R statistical packages.	Factor scores are standard scores (Mean =0, Variance = SMC) Produces unbiased estimates. In an orthogonal solution, factor scores are not correlated with other factors (univocality). Procedure produces high validity estimates.	The scores may be correlated even when factors are orthogonal.
Anderson-Rubin	Method of producing factor scores is similar to Bartlett, but allows factor scores to be uncorrelated when factors are orthogonal. Can be computed using SPSS.	Factor scores have a mean of 0, have a standard deviation of When the factors are orthogonal, factor scores are uncorrelated as well (correlational accuracy). Factor scores have reasonably high correlations with their estimated factor (validity).	Factor scores may be correlated with the other orthogonal factors (i.e. not univocal). Factor scores are not unbiased.

Note. Adopted from “Understanding and Using Factor Scores: Considerations for the Applied Researcher,” by DiStefano, C., Zhu, M., & Mindrila, D., 2009, *Practical Assessment, Research & Evaluation, 14*(20), p.9.

General Linear Model Analyses

The definition of general linear model (GLM) analysis is that there can be one or multiple predictors' variables which can be either categorical or quantitative. In current study, researchers used MAONVA to test hypothesis 2-5, logistic regression analysis to test hypothesis 6, and multiple linear regression to test hypothesis 7.

Multivariate Analysis of Variance (MANOVA)

Multivariate analysis of variance (MANOVA) was used to test hypotheses 2-5. In the current study, researchers used MANOVA to compare whether the means of students' career development in college and new graduates' career barriers in workforce significantly differ across multiple groups. The equations of MANOVA can be represented as a list of vector Y outcome variables. Specifically, μ_k represents the vector or a set of means on different outcome variables among k groups, and the null hypothesis for one-way MANOVA can be written as fellows (Warner, 2008):

$$H_o: \mu_1=\mu_2=\ldots\ldots\ldots\ldots\ldots\ldots\mu_k$$

$$H_0 = \begin{matrix} u_{11} \\ \vdots \\ u_{1p} \end{matrix} = \begin{matrix} u_{21} \\ \vdots \\ u_{2p} \end{matrix} = \cdots = \begin{matrix} u_{k1} \\ \vdots \\ u_{kp} \end{matrix}$$

where

k= The number of group (i.e. three different employment statuses in the current study)

p= The number of outcome variables (i.e. career development variables, career barriers in the current study)

u_{1p} = The mean of group 1 for p variable

u_{pk} = The mean of group k for p variable

Box's M test

For MANOVA, researchers chose several analyses to test hypotheses. First, researchers performed Box's M test and/or the Leven test for checking the serious violations of the assumption of homogeneity of variances and covariance across groups. The problems of violation of this assumption may increase the risk of a Type I error and reduce statistical power particularly when any group's sample size is small or extremely unequal among groups. The assumption of homogeneity of the variance/covariance matrices cross groups can be written as follows (Warner, 2008):

$$\mathrm{H}_0\!: \sum\nolimits_1 = \sum\nolimits_2 = \cdots = \sum\nolimits_k$$

Power Analysis and Sample Size Test

Researchers developed codes for ANOVA power analysis in SAS to test efficiency of the sample size while performing MANOVA. The code of power analysis was shown in Appendix B.

Multivariate Test Statistics

In current study, researchers preferred to use Wilks's Λ and Hoteling's trace to test multivariate statistics across groups for hypotheses 2-8. Wilks's Λ and could be used to calculate effect size (η^2) for MANOVA.

All equations were shown below (Warner, 2008):

$$SS_{between} = \sum_{i=1}^{k} n_i (M_i - M_y)^2$$

$$SS_{within} = \sum_{i=1}^{k} SS_i = SS_1 + SS_2 \ldots + SS_k$$

$$SS_{total} = \sum_{i=1}^{k}\sum_{j=1}^{n_k}(Y_{ij} - M_y)^2$$

$$\lambda_i = \frac{SS_{between}}{SS_{within}}$$

$$\text{Wilks's } \Lambda = \prod[1/(1+\lambda_i)]$$

$$\eta^2 = 1 - \Lambda$$

Where

$SS_{between}$=	The sum of the squared deviations of each score from the grand mean.
SS_{within}=	The sum of squared deviations of each score from its group mean.
SS_{total}=	The sum of squared deviations of each score from among group means.
M_i =	The mean of i group
M_y =	The grand mean
n_i =	The same size of i group
Y_{ij}=	The score of j subject number in group i.
λ_i=	Eigenvalue of i group
η^2 =	Effect size

Logistic Regression Analysis

Researchers used power analysis in SAS to test the sample size of logic regression in SAS. The code of power analysis was shown in Appendix B. Logistic Regression is used when the outcome variable is a categorical variable, and the goal is prediction of group membership. The categorical dependent/outcome variable could be a binary, ordinal, nominal or count variable (Park, 2005). In the current study, researchers used logistic regression to test hypothesis

6. While confidence statistic equals 1 represented that the model is perfectly fit. Therefore, the concordant statistic of a model should be greater than .5 (Bruin, 2006). The outcome variable is a nominal variable (employment status coded 1: full time STEM employed and 0: under/un-employed). The equation can be written as follows:

$$L_i = \ln\left[\frac{p_i}{1-p_i}\right] = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots\ldots \beta_k X_k$$

or

$$p_i = \frac{e^{\beta_0+\beta_1 X_1+\cdots\beta_k X_k}}{1+e^{\beta_0+\beta_1 X_1+\cdots\beta_k X_k}}$$

where

p_i= The estimated probability that person i is a member of the "target" outcome group that corresponds to a code of 1 (rather than the group that is coded 0).

β_0= The intercept

β_k= The regression coefficient that are applied to raw score $X_k$on the predictor variable k

Multiple Linear Regressions

Researchers used power analysis in SAS to test the sample size of multiple linear regressions in SAS. The code of power analysis was shown in Appendix B. Multiple linear regression is used when the outcome variable is a constituted variable, and the goal is prediction of the outcome variable (i.e. GPAs). In the current study, researchers used multiple linear regressions to test hypothesis 7. The equation can be written as follows:

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} + \ldots\ldots \beta_p X_{ip} + \varepsilon_i$$

where

Y_i= The i^{th} participant (i.e. i = total sample) responses from the dependent variables

X_{ik}= The raw score value of i^{th} participant of the k^{th} independent variable, $k = 1, .., p$.

β_0= The intercept

β_k= The regression coefficient or the rate of change that are applied to raw score $X_k$on the kth predictor variable, $k = 1, \ldots, p$.

ε_i= The error, the errors are independent and identically normal $N(\mu, \sigma^2)$.

i= $i = 1, .., p$.

Power Analysis and Sample Size Test

Values of power range from 0 (low power) to 1(high power). There are many ways to determine the minimum number of subjects for conducing GLM analyses. A previous study suggested that a rule-of-thumb of determining the number of subjects based on the effect sizes (R^2). Cohen (1988) suggested to calculate sample size was $N \geq (8/f^2) + (m - 1)$, where f is $(1 - {R_{\text{adj}}}^2)$ and m is the total number of predictors (Green, 1991). In addition, researchers also used a power analysis package in SAS. The detail of code of power analysis is shown in Appendix B.

Multicollinearity diagnostic

Multicollinearity is referred to the degree of intercorrelation among predictor variables. Researchers suggest that if the correlation between two predictors is more than .9, they are actually measures of the same construct (Warner, 2008). When one outcome variable is predictable by more than one predictor variable, multicollinearity diagnostic should be included in data analysis. Researchers suggest the best rang of collinearity is less than 2.5 (Coumarbatch, Robinson, Thomas, & Bridge, 2010). If the collinearity of any predictor is greater than 2.5 it may drop one of the variables from the model. Alternative way is to combine their scores of highly correlated variables into a single variable by summing or averaging them (Warner, 2008).

CHAPTER 4

RESULTS

The purpose of current study was to develop an assessment to measure STEM higher education students' career development for predicting their employment status and career barriers in the STEM workforce. Based on Rae's theoretical model (2007), researchers created 58 items based on five career development domains (i.e. personal development, applied learning, skill development, work-based learning, and career management) for assessing students' career development (i.e. employability) in STEM higher education. This chapter presents the results of the research performed in this study. It provides a detail of all data analysis for testing hypotheses 6 and 7 encapsulated in the models.

Participants and Demographics

The majority of participants were 62.8 % male and 62.1% Caucasian (11.5 % Asian, 10.2 % African American, 5.7% Hispanic, and 13.4 % others). Overall, 23.6% participants were majored in science, 12.5% majored in technology, 52.1% majored in engineering, and 11.8 % majored in mathematics. The mean age is 24.3 (SD=4.65). There were 11.7 % of participants who have ever taken career and technical education (CTE) course(s) and 36.6% ever utilized career service in the university before. Based on a new graduates' report, 39.5% of new STEM graduates (graduated within one year) were full-time employed, 36.8% were unemployed/underemployed, and 23.7% were currently enrolled in graduate school. Specifically, 50% (n=12) of new graduates that majored in science, 80 % (n=5) of new graduates majored in technology, 25 % (n=16) of new graduates majored in engineering, and 20% (n=5) of new graduates majored in mathematics were full-time employed. The participant demographics are presented in Table 8.

Table 8

Frequencies and Percentages for Participants' Characteristics

Variable	N	%
Participants		
New Graduates(alumni)	35	24.3
Current Students	109	75.6
Total	146	100.0
Age	Mean= 24.3 (SD=4.6)	
Gender		
Male	91	62.8
Female	53	36.6
Total	146	100.0
Race		
Caucasian	93	62.1
Asian American	18	11.5
African American	16	10.2
Hispanic	9	5.7
Others		13.4
CTE (Career Technical Education)		
Took Before	17	11.7
Never	128	88.3
Total		
Career Service		
Used before	53	36.6
Never	92	63.4
Total		
STEM Majors		
Science related majors	34	23.4
Technology related majors	18	12.4
Engineering related majors	75	51.7
Mathematics related majors	17	11.7
Total		
Employment Status		
Full-time employed	15	39.5
Unemployed/underemployed	14	36.8
Graduated students	9	23.7
Total		

Normality Distributions Test for All Variables

There were many ways to test normality of variables. Many studies suggested using the Shapiro-Wilk test to estimate normality of variables. The null hypothesis of the Shapiro-Wilk test is that data is normally distributed. Although all 58 items were not normally distributed based on the Shapiro-Wilk test, researchers presented an alternative way for determining whether data could be seen as normally distributed. According to other studies, researchers suggested that the acceptable limits of the skewness and kurtosis are ±1.96 (Trochim & Donnelly, 2006; Field, 2000 & 2009; Gravetter & Wallnau, 2014). In the current study, three items' kurtosis were in excess of 1.96 including SD07, SD15 and SD19 items (Table 9).

Table 9

Career Development Assessment Normal Distribution Test

Variable		*df*	Sig.	Skewness	Kurtosis
PD01	…set my personal learning	145	.000	-.83	.45
PD02	…reflect my personal learning	145	.000	-.88	.97
PD03	…produce useful documents	145	.000	-.56	-.39
PD04	…assess my personal learning	145	.000	-.80	.41
PD05	....make connections	145	.000	-1.09	.92
PD06	....apply theoretical knowledge	145	.000	-1.14	1.56
PD07	…transfer knowledge	145	.000	-.78	.33
AL01	…show evidence of applied	145	.000	-.72	-.31
AL02	... transfer skills from academia	145	.000	-.66	.09
AL03	…opportunities to speak	145	.000	-.75	.01
AL04	....presentations from guest	145	.000	-.75	-.19
AL05	....participation in live case	145	.000	-.37	-.76
AL06	…interactive and simulation	145	.000	-.23	-.74
SD01	....self-organization	145	.000	-.66	-.11
SD02	....time management	145	.000	-.90	.35
SD03	…budgeting	145	.000	.11	-.85
SD04	…finding opportunities	145	.000	-.78	.27
SD05	…taking the initiative	145	.000	-.84	.90
SD06	…creative thinking	145	.000	-.78	-.05

Table 9. Career Development Assessment Normal Distribution Test (Continued)

	Variable	***df***	**Sig.**	**Skewness**	**Kurtosis**
SD07	…problem solving	145	.000	-1.56	3.16
SD08	…verbal communication	145	.000	-.94	.64
SD09	…written communication	145	.000	-1.14	1.66
SD10	…interpersonal relationship	145	.000	-.68	.07
SD11	…negotiation	145	.000	-.22	-.67
SD12	....persuasion	145	.000	-.29	-.69
SD13	…leadership	145	.000	-.76	.49
SD14	…project management	145	.000	-.80	.72
SD15	…numerical, analytical	145	.000	-1.46	2.32
SD16	....computer skills	145	.000	-1.05	.78
SD17	....professionalism	145	.000	-.87	.98
SD18	....make plans	145	.000	-1.06	1.25
SD19	…set goals	145	.000	-1.43	2.65
SD20	…achieve goals	145	.000	-1.17	1.92
SD21	….make decisions	145	.000	-1.08	1.56
SD22	.....accept risks in conditions	145	.000	-.76	.23
SD23	….work independently	145	.000	-1.31	1.62
SD24	.....take responsibility	145	.000	-1.32	1.87
SD25	….apply academic learning	145	.000	-.73	.24
SD26	….adapt and work flexibly	145	.000	-.93	.67
SD27	….participate in social	145	.000	-.58	-.09
SD28	.....work effectively	145	.000	-1.14	1.28
SD29	….take responsibility	145	.000	-.97	.92
SD30	….my self-confidence	145	.000	-.88	.54
SD31	….my self-efficacy	145	.000	-1.22	1.59
WB01	….short-term work experience	145	.000	.12	-1.10
WB02	….full academic year	145	.000	.06	-1.16
WB03	….relevant part-time	145	.000	.05	-1.06
WB04	….voluntary, community	145	.000	-.23	-1.03
WB05	.....self-employment	145	.000	.18	-.85
WB06	….leadership or organization	145	.000	-.71	-.21
CM01	.....resume or curriculum vitae	145	.000	-.87	.10
CM02	….job searching.	145	.000	-.86	.13
CM03	….self-professional skills.	145	.000	-.94	.61
CM04	….communication skills.	145	.000	-1.07	1.35
CM05	.....career guidance.	145	.000	-.61	-.16
CM06	….access to industry	145	.000	-.82	.34
CM07	.....access to professional	145	.000	-1.00	.64
CM08	….access to professional	145	.000	-.88	.38

Exploratory Factor Analysis

The objectives of performing exploratory factor analysis in the current study were to (1) test and reduce the number of domains and variables of students' career development assessment, (2) evaluate validity of assessment, and (3) modify and prove the theoretical model based on the data. Based on Rae's career development model (2007), researchers selected its 40 principles to develop five sub-scales (i.e. personal development, applied learning, skill development, work-based learning, and career management) with 58 items measuring construct. Exploratory factor analysis was used to test whether these items work together. The results indicated there were 33 items and four factors retained after performing exploratory factor analysis. In the following sections, researchers provide a detail of developing the career development assessment.

Convergent Validity Test

Researchers used multiple ways to determine if the items for the scales had convergent validity. First, the results of KMO and Bartlett's Tests from performing exploratory confirmatory factor analysis with Varimax rotation were indicated that the Kaiser-Meyer-Olkin Measure of Sampling Adequacy test was above .9 and Bartlett's Tests was significant According to previous studies, KMO > .9 and Bartlett's Test <.000 (see Table 10) which means the correlations among the variables are all significant, together were referred to the data is very suitable to perform factor analysis (Cerny & Kaiser, 1977). The detail of the composite construct reliability and the individual item reliability were shown in Table 11 and Table 12. Individual item reliability was above .9 (standard $\geq$ 0.5), the composite construct reliability was above .85 (standard $\geq$ 0.7). The results of both reliability tests support the convergent validity.

Table 10

KMO Test and Barlett's Test of Sphericity

Tests	Statistic	Chi-Square	Sig
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	.911	4105.934	*
Bartlett's Test of Sphericity	*	*	.000

Table 11

Career Development Composite Scale' Reliability

Variable	Mean	Std.	Items	Possible Range	Cronbach's Alpha
Skill Development (SD)	4.05	.722	18	1-5	.960
Work-based Learning (WB)	2.89	1.15	5	1-5	.917
Career Management (CM)	3.75	.890	6	1-5	.908
Applied Learning Domains (AL)	3.56	.913	4	1-5	.854

Table 12

Career Development Individual Item Reliability

	Variable	Accepted	Mean	SD.	Possible Range	Cronbach's Alpha
PD01	…set my personal		3.88	.99	1-5	.974
PD02	…reflect my personal		3.83	.93	1-5	.974
PD03	…produce useful		3.69	1.09	1-5	.974
PD04	…assess my personal		3.76	1.00	1-5	.974
PD05	....make connections		3.99	1.02	1-5	.974
PD06	....apply theoretical		4.03	.94	1-5	.974
PD07	…transfer knowledge		3.81	.99	1-5	.974
AL01	…show evidence of	√	3.95	1.00	1-5	.974
AL02	....transfer skills from	√	3.66	1.01	1-5	.974
AL03	…opportunities to speak		3.78	1.08	1-5	.975
AL04	....presentations from		3.78	1.12	1-5	.975
AL05	....participation in live	√	3.37	1.20	1-5	.974
AL06	…interactive and	√	3.27	1.17	1-5	.974
SD01	....self-organization		3.76	1.06	1-5	.975
SD02	....time management		3.85	1.09	1-5	.974
SD03	…budgeting		2.88	1.22	1-5	.975
SD04	…finding opportunities		3.75	1.06	1-5	.974
SD05	…taking the initiative		3.79	.97	1-5	.974
SD06	…creative thinking		3.92	1.06	1-5	.974
SD07	…problem solving	√	4.37	.82	1-5	.974
SD08	…verbal communication	√	3.98	1.00	1-5	.974
SD09	…written communication	√	4.08	.90	1-5	.974
SD10	…interpersonal		3.59	1.04	1-5	.974
SD11	…negotiation		3.14	1.12	1-5	.974
SD12	....persuasion		3.26	1.12	1-5	.974
SD13	…leadership	√	3.78	.99	1-5	.974
SD14	…project management		4.00	.88	1-5	.974
SD15	…numerical, analytical	√	4.34	.86	1-5	.974
SD16	....computer skills		3.99	1.01	1-5	.974
SD17	....professionalism	√	4.02	.87	1-5	.974
SD18	....make plans	√	3.99	.92	1-5	.974
SD19	…set goals	√	4.14	.91	1-5	.974
SD20	…achieve goals	√	4.14	.85	1-5	.974
SD21	…make decisions	√	4.14	.86	1-5	.974
SD22	....accept risks in	√	3.87	.98	1-5	.974
SD23	…work independently	√	4.17	.97	1-5	.974
SD24	....take responsibility	√	4.17	.95	1-5	.974
SD25	…apply academic		3.79	1.02	1-5	.974
SD26	…adapt and work flexibly	√	3.94	.99	1-5	.974

Table 12

Career Development Individual Item Reliability (continued)

	Variable	Accepted	Mean	SD.	Range	Cronbach's Alpha
SD27	…participate in social		3.63	1.03	1-5	.974
SD28	....work effectively	√	4.08	.94	1-5	.974
SD29	…take responsibility	√	4.01	.97	1-5	.974
SD30	…my self-confidence	√	3.81	1.05	1-5	.974
SD31	…my self-efficacy	√	3.94	1.01	1-5	.974
WB01	…short-term work	√	2.86	1.35	1-5	.975
WB02	…full academic year	√	2.82	1.39	1-5	.975
WB03	…relevant part-time	√	2.90	1.32	1-5	.975
WB04	…voluntary, community	√	3.17	1.32	1-5	.974
WB05	....self-employment	√	2.68	1.25	1-5	.975
WB06	…leadership or		3.71	1.18	1-5	.974
CM01	....resume or curriculum	√	3.80	1.13	1-5	.975
CM02	…job searching.	√	3.65	1.12	1-5	.975
CM03	…self-professional skills	√	3.70	1.06	1-5	.974
CM04	…communication skills		3.91	.96	1-5	.974
CM05	....career guidance.		3.56	1.07	1-5	.974
CM06	…access to industry	√	3.68	1.04	1-5	.974
CM07	....access to professional	√	3.95	1.04	1-5	.974
CM08	…access to professional	√	3.76	1.06	1-5	.974

Factor Dimensionality and Communality

The principal components analysis (PCA) procedure was used to extract the factors from the data. This process is called discriminant validity test for obtaining unique component. Based on the screen plot and the variance from the results of exploratory factor analysis (Figure 3 and Figure 4), it was shown that the elbow points' eigenvalue is 1.6 in the current study. Although researchers tried to retain 5 factors to satisfy the total account above 70 % of the variance, the fifth factor had only 2 observed variables which is violated factor analysis that each factor have at least three items (O'Rourke & Hatcher, 2013). Hence, four factors with 33 items were retained, and they were most eligible for interpretation because this rule requires that a given factor is capable of explaining at least the equivalent of one variable's variance. Together the proportion of the total variation explained by the four factors is 66.94% (see Table 13).

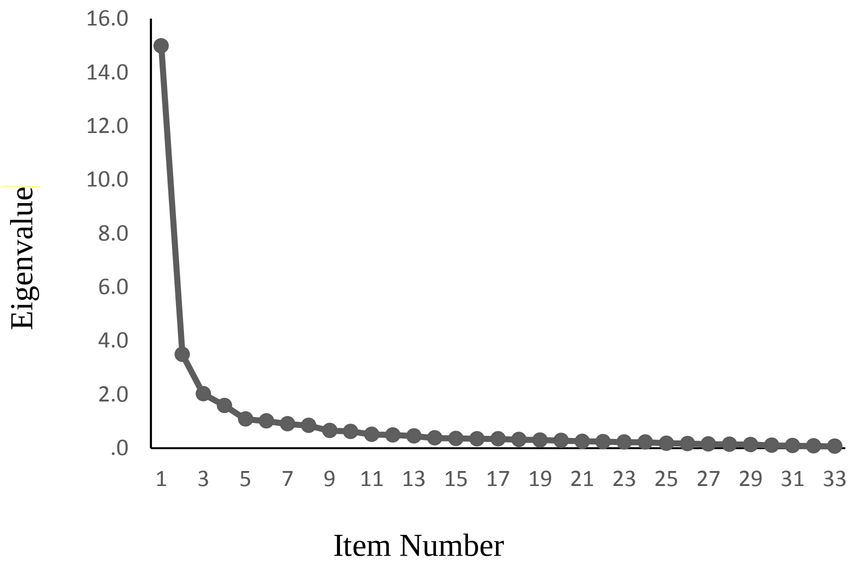


Figure 3. The Screen plot of exploratory factor analysis

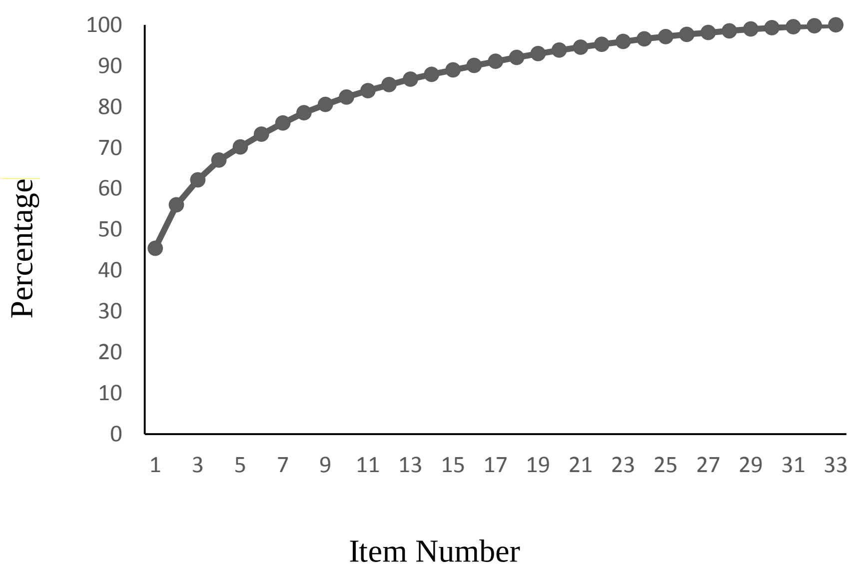


Figure 4. The variance explained of exploratory factor analysis

Table 13

Variances Explained by Factors

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	**%V.**	**% C.**	**Total**	**%V.**	**% C.**	**Total**	**%V.**	**% C.**
1	14.99	45.42	45.42	14.99	45.42	45.42	10.32	31.28	31.28
2	3.49	10.59	56.01	3.49	10.59	56.01	4.27	12.93	44.21
3	2.02	6.12	62.12	2.02	6.12	62.12	4.21	12.76	56.97
4	1.59	4.81	66.94	1.59	4.81	66.94	3.29	9.97	66.94
5	1.08	3.26	70.20						
6	1.01	3.07	73.27						
7	0.90	2.73	76.00						
8	0.84	2.54	78.55						
9	0.65	1.98	80.53						
10	0.62	1.87	82.40						
11	0.51	1.53	83.93						
12	0.49	1.47	85.40						
13	0.45	1.36	86.76						
14	0.38	1.16	87.92						
15	0.36	1.08	89.00						
16	0.35	1.08	90.08						
17	0.34	1.02	91.09						
18	0.32	0.97	92.07						
19	0.30	0.91	92.98						
20	0.28	0.84	93.82						
21	0.25	0.75	94.57						
22	0.24	0.72	95.29						
23	0.22	0.67	95.96						
24	0.22	0.65	96.62						
25	0.18	0.56	97.17						
26	0.17	0.53	97.70						
27	0.15	0.45	98.15						
28	0.14	0.42	98.58						
29	0.13	0.40	98.98						
30	0.10	0.31	99.29						
31	0.09	0.27	99.56						
32	0.08	0.24	99.80						
33	0.07	0.20	100.00						

Note: Extraction Method: Principal Component Analysis. V. = Variance, C. = Communality

The component matrix contains the loading of each variable onto each factor before performing the function of rotation. Researchers requested that all loading less than 0.5 be suppressed in the output; therefore, there are blank spaces for many of the loading. However, the matrix is not particularly important. As seen in Tables 14-17. The Skill Development items were all highly correlated with each other in component 1 with correlations ranging from .45 to .59. The Work-based Learning were moderately correlated with each other in component 1 and also highly correlated with component 2. The Career Management items were correlated with each other in component 1 with correlations ranging from .53 to .75 except CM1 and CM2 items were also highly correlated with component 3. Finally, the Apply Learning items were highly correlated with each other in component 1 correlations ranging from .56 to .62.

Table 14

Component Matrix Perceived Skill Development

	Component			
Item	1	2	3	4
SD7	.69			
SD8	.75			
SD9	.70			
SD13	.74			
SD15	.63			
SD17	.74			
SD18	.70			
SD19	.82			
SD20	.77			
SD21	.83			
SD22	.76			
SD23	.75			
SD24	.77			
SD26	.75			
SD28	.76			
SD29	.75			
SD30	.68			
SD31	.71			

Table 15

Component Matrix Perceived Work-based Learning

Item	Component 1	2	3	4
WB1	.51	**.63**		
WB2	.49	**.68**		
WB3	.52	**.61**		
WB4	**.59**			
WB5	.45	**.65**		

Table 16

Component Matrix Perceived Career Management

Item	Component 1	2	3	4
CM1	.55		**.60**	
CM2	.53		**.57**	
CM3	**.67**			
CM6	**.61**			
CM7	**.75**			
CM8	**.69**			

Table 17

Component Matrix Perceived Apply Learning

Item	Component 1	2	3	4
AL1	.59			
AL2	.62			
AL5	.56			
AL6	.58			

The results of communalities show all variance in common before and after extraction (see Table 18). The average variance extracted is .669 which is above the standard (.5 or above). Researchers suggested that average variance extracted (AVE) should be larger than .5 (Fornell and Larcker 1981).

Table 18

Extraction of Communalities by Items

	Communalities	
Item	Initial	Extraction
AL1	1.000	.707
AL2	1.000	.685
AL5	1.000	.642
AL6	1.000	.701
SD7	1.000	.620
SD8	1.000	.591
SD9	1.000	.563
SD13	1.000	.566
SD15	1.000	.525
SD17	1.000	.585
SD18	1.000	.582
SD19	1.000	.782
SD20	1.000	.705
SD21	1.000	.753
SD22	1.000	.651
SD23	1.000	.757
SD24	1.000	.714
SD26	1.000	.580
SD28	1.000	.647
SD29	1.000	.669
SD30	1.000	.506
SD31	1.000	.574
WB1	1.000	.765
WB2	1.000	.777
WB3	1.000	.798
WB4	1.000	.678
WB5	1.000	.725
CM1	1.000	.734
CM2	1.000	.753
CM3	1.000	.699
CM6	1.000	.583
CM7	1.000	.764
CM8	1.000	.708

Note: Extraction method: Principal component analysis

Discriminant Validity

Orthogonal rotation was used to test if the factors were uncorrelated. Oblique, on the other hand, was used to test if these factors were correlated. In SAS and SPSS, Varinmax was the function to perform the orthogonal rotation, and Promax was used for Oblique function. Both rotation methods were performed to test which rotation could produce the best outcomes.

Rotation

After trying different rotation methods, researchers chose the Varimax rotation method for getting the best results. As seen in Table 19, the Applied Learning (AL) items, the Skill Development (SD) items, the Work-based Learning (WB) items, and the Career Management (CM) items were loaded most highly on different factors. The Skill Development items were loaded most highly on Factor 1; the Work-based Learning items were most highly loaded on Factor 2; the Career Management items were loaded on Factor 3 and the Applied Learning items were most highly loaded on Factor 4. The extraction sum of squares loadings was 66.94%. In the context of this study, researchers demonstrated the validity with evidence supporting the conclusion that the factor scores following successive tests. Researchers summarized different rotation methods their variance by items and factors (see Table 20).

Factor Score Computation

After comparing the results of each factor computation methods, three were no differences of using different factor score computation. Therefore, researchers chose sum scores of each factor divided by totals item to compute the factor score. Each variable can be explained by the factors. The following equations represented the computation of each factor:

$$F_{SD} = (SD_7 + SD_8 + SD_9 + SD_{13} + SD_{15} + SD_{17} + SD_{18} + SD_{19} + SD_{20} + SD_{21} + SD_{22} + SD_{23} + SD_{24} + SD_{26} + SD_{28} + SD_{29} + SD_{30} + SD_{31})/18$$

$F_{WB} = (WB_1 + WB_2 + WB_3 + WB_4 + WB_5)/5$

$F_{CM} = (CM_1 + CM_2 + CM_3 + CM_6 + CM_7 + CM_8)/6$

$F_{AL} = (AL_1 + AL_2 + AL_5 + AL_6)/4$

The following equations represent each observed variable as being a weighted sum of the underlying factors:

$$x_1 = \beta_{11}F_{SD} + \beta_{21}F_{WB} + \beta_{31}F_{CM} + \beta_{41}F_{AP} + \varepsilon_1$$

$$x_2 = \beta_{12}F_{SD} + \beta_{22}F_{WB} + \beta_{31}F_{CM} + \beta_{42}F_{AP} + \varepsilon_2$$

$$\vdots$$

$$x_m = \beta_{1m}F_1 + \beta_{2m}F_2 + \beta_{3m}F_{CM} + \beta_{4m}F_{AP} + \varepsilon_m$$

Table 19

Rotated Component Matrix Perceived Career Management

	Component			
Item	1	2	3	4
AL1				**.762**
AL2				**.713**
AL5				**.699**
AL6				**.748**
SD7	**.764**			
SD8	**.642**			
SD9	**.598**			
SD13	**.639**			
SD15	**.629**			
SD17	**.653**			
SD18	**.725**			
SD19	**.836**			
SD20	**.788**			
SD21	**.781**			
SD22	**.744**			
SD23	**.830**			
SD24	**.815**			
SD26	**.658**			
SD28	**.741**			
SD29	**.786**			
SD30	**.622**			
SD31	**.682**			
WB1		**.833**		
WB2		**.835**		
WB3		**.855**		
WB4		**.732**		
WB5		**.819**		
CM1			**.820**	
CM2			**.823**	
CM3			**.702**	
CM6			**.631**	
CM7			**.706**	
CM8			**.698**	

Table 20

Comparison of Extraction and Rotation Methods (n= 145)

Rotation Method		Principal Components: Orthogonal (Varimax)	Principal Components: Oblique (Promax)	Maximum Likelihood: Orthogonal (Varimax)	Maximum Likelihood: Oblique (Promax)
		Variance Accounted after Rotation			
Items Loadings		66.94% (√)	66.94%	61.41%	61.41%
Factor 1	SD07	.764	.862	.698	.730
	SD08	.642	.589	.609	.724
	SD09	.598	.528	.614	.687
	SD13	.639	.622	.638	.723
	SD15	.629	.635	.646	.666
	SD17	.653	.614	.674	.749
	SD18	.725	.789	.748	.764
	SD19	.836	.900	.840	.882
	SD20	.788	.842	.817	.839
	SD21	.781	.790	.834	.879
	SD22	.744	.800	.713	.783
	SD23	.830	.944	.746	.798
	SD24	.815	.908	.738	.799
	SD26	.658	.654	.635	.724
	SD28	.741	.777	.684	.765
	SD29	.786	.856	.747	.788
	SD30	.622	.645	*	.626
	SD31	.682	.737	*	.671
Factor 2	WB1	.833	.859	.836	.338
	WB2	.835	.853	.846	.295
	WB3	.855	.892	.818	.346
	WB4	.732	.725	.693	.450
	WB5	.819	.848	.785	.274
Factor 3	CM1	.820	.930	.711	.425
	CM2	.823	.930	.713	.367
	CM3	.702	.720	.626	.537
	CM6	.631	.639	.653	.469
	CM7	.706	.710	.736	.644
	CM8	.698	.706	.755	.555
Factor 4	AL1	.762	.862	.453	.536
	AL2	.713	.773	*	.510
	AL5	.699	.768	*	.449
	AL6	.748	.832	*	.470

General Linear Model Analyses

First, researchers performed multivariate analysis of variance (MANOVA) to test hypotheses 2-5. Descriptive analysis, normality, and power analysis were tested before testing MANOVA.

Descriptive Analysis

Career Development Assessment

There were 33 questions on the Career Development assessment with four sub-scales including skill development, work-based learning, career management, and applied learning sub-scales. Researchers chose non-refined method, the sum of factor scores, divided by total items to create the four sub scales (skill development, work-based learning, career management, and applied learning) for assessing students' career development in STEM higher education. Cronbach's alpha coefficient (α) for career development assessment indicated that skill development (.959), work-based learning (.917), career management (.908), and applied learning (.851) sub-scales had good reliability and internal consistency.

Career Barriers Assessment

Career barriers were used to assess new graduates' current career experiences in workforce. In the current study, researchers only focused on six domains including lack of confidence, inadequate preparation, decision-making difficulties, dissatisfaction with career, job market constraints, and difficulty with networking. The original Cronbach's alpha coefficient (α) for the revised career development career barriers assessment scales range from .64 to .86 (Swanson & Daniels, 1996). In current study, the Cronbach's alpha of each sub-scales ranged from .685 to .947 (lack of confidence =.782, inadequate preparation =.685, decision-making difficulties= .947, dissatisfaction with career =.861, job market constraints =.817, and difficulty with networking = .896). The mean and standard deviation of each variable was shown in Table 21.

Table 21

Career Development and Career Barriers Assessments' Internal Reliability

Variable	Mean	Std.	Items	Possible Range	Cronbach's Alpha
Career Development					
Skill Development (SD)	4.05	.72	18	1-5	.960
Work-based Learning (WB)	2.89	1.20	5	1-5	.917
Career Management (CM)	3.75	.89	6	1-5	.908
Applied Learning (AL)	3.56	.91	4	1-5	.854
Career Barriers					
Lack of confidence (LC)	2.09	.84	4	1-5	.782
Inadequate preparation (IP)	2.21	.74	5	1-5	.685
Decision-making difficulties (DM)	2.07	.99	8	1-5	.974
Dissatisfaction with career (DC)	1.93	.78	5	1-5	.861
Job market constraints (JMC)	2.05	.95	4	1-5	.817
Difficulty with networking (DN)	2.15	.97	5	1-5	.896
Overall GPA	144	3.22	1	*	*

Normality Test

The overall normality test for career development assessment (four factors with 33 items), career barriers (six sub-scales), and GPA indicated that only two sub-scales (i.e. lack of confidence and inadequate preparation) are normally distributed based on Shapiro-Wilk test. Using the acceptable limits of the skewness and kurtosis' criteria (Trochim & Donnelly, 2006; Field, 2000 & 2009; Gravetter & Wallnau, 2014), only the kurtosis of the skill development is in excess of 1.96 (Table 22).

Table 22

Descriptive Analysis for the Sub-scales of Career Development Assessment, Career Barriers, and GPA (Overall)

Variable	*N*	Mean	SD.	Skewness	Kurtosis
Career Development					
Skill development	145	4.05	.72	-1.488	2.886
Work-based learning	145	2.89	1.15	.038	-.723
Career management	145	3.76	.89	-.906	.826
Applied learning	145	3.56	.91	-.359	-.294
Career Barriers					
Lack of confidence	38	2.09	.84	.566	-.517
Inadequate preparation	22	2.21	.74	-.214	-1.082
Decision-making difficulties	22	2.07	.99	.794	-.283
Dissatisfaction with career	38	1.93	.78	.459	-.623
Job market constraints	38	2.05	.95	.524	-1.072
Difficulty with networking	38	2.15	.97	.717	-.286
Overall GPA	144	3.22	.49	-.364	-.838

Furthermore, researchers also performed normality test for career development, career barriers, and overall GPA variables by four separated categorical variables including CTE (1: took CTE, 0: never take CTE), CS (1: utilized career service; 0: never used), STEM majors (1: Science, 2: Technology, 3: Engineering, 4: Mathematics), and employment status (1: full-time STEM employed, 0: not full-time STEM employed). The results of skewness and kurtosis including their descriptive analysis are shown from Table 23 to Table 26. Based on the alternative skewness and kurtosis' criteria (Trochim & Donnelly, 2006; Field, 2000 & 2009; Gravetter & Wallnau, 2014), skill development is not normal distributed in test CTE, CS, and

STEM majors groups. Applied learning is not normally distributed in CTE group, and decision-making difficulties is not normally distributed in the not full-time employment group.

Table 23

Normality Test and Descriptive Analysis for the Sub-scales of Career Development Assessment, GPA, and Career Choice by CTE and non-CTE groups

Variable	*N*	Taking CTE	Mean	SD.	Skewness	Kurtosis
Career Development						
Skill development	17	Yes	4.41	.56	-.927	.679
	128	No	4.00	.73	-1.52	3.895
Work-based learning	17	Yes	3.49	.99	.511	-.846
	128	No	2.80	1.15	.053	-.805
Career management	17	Yes	4.15	.77	-.444	-1.259
	128	No	3.70	.89	.214	.425
Applied learning	17	Yes	3.78	.73	.195	-.641
	128	No	3.53	.93	-.354	-.370
Overall GPA	16	Yes	3.22	.54	-.611	-.991
	128	No	3.22	.49	-.333	-.807

Table 24

Normality Test and Descriptive Analysis for the Sub-scales of Career Development Assessment, and GPA by CS and non-CS groups

Variable	*N*	Utilizing CS	Mean	SD.	Skewness	Kurtosis
Career Development						
Skill development	53	Yes	4.19	.59	-.981	1.562
	92	No	3.98	.78	-1.503	3.641
Work-based learning	53	Yes	2.87	1.11	.239	-.608
	92	No	2.89	1.18	-.057	-.756
Career management	53	Yes	4.03	.66	-.545	.464
	92	No	3.60	.97	-.765	.262
Applied learning	53	Yes	3.74	.84	-.582	.351
	92	No	3.46	.94	-.221	-.451
Overall GPA	53	Yes	3.18	.49	-.294	.847
	92	No	3.25	.49	-.416	-.797

Table 25

Normality Test and Descriptive Analysis for the Sub-scales of Career Development Assessment, and GPA by STEM Majors

Variable	*N*	Major	Mean	SD.	Skewness	Kurtosis
Career Development						
Skill development	34	Science	4.22	.65	-.931	1.117
	17	Technology	4.16	.57	-.139	-.806
	75	Engineering	3.98	.64	-.992	1.460
	17	Mathematics	4.11	.93	-2.47	7.92?
Work-based learning	34	Science	3.35	1.16	-.316	.497
	17	Technology	2.98	1.08	.750	-.170
	75	Engineering	2.77	1.13	.093	-.772
	17	Mathematics	2.51	1.05	-.546	-1.498
Career management	34	Science	3.69	.95	-.969	.666
	17	Technology	3.74	.72	-.415	1.013
	75	Engineering	3.94	.73	-.503	-.078
	17	Mathematics	3.25	1.17	-.371	-.652
Applied learning	34	Science	3.86	.922	-.185	-1.386
	17	Technology	3.63	.91	-.731	.764
	75	Engineering	3.48	.80	-.357	-.103
	17	Mathematics	3.41	1.12	-.203	-1.034
Overall GPA	34	Science	3.17	.52	-.031	-1.199
	17	Technology	3.10	.50	-.494	-1.169
	75	Engineering	3.23	.47	-.461	-.579
	17	Mathematics	3.47	.44	-.945	.891

Table 26

Normality Test and Descriptive Analysis for the Sub-scales of Career Development Assessment, and GPA by Employment Status

Variable	*N*	Full-Time Employed	Mean	SD.	Skewness	Kurtosis
Career Development						
Skill development	15	Yes	4.58	.40	-.503	-1.451
	15	No	3.96	.80	-1.18	1.24
Work-based learning	15	Yes	3.64	1.23	-.167	-1.481
	15	No	2.25	.88	.312	-.875
Career management	15	Yes	4.16	.57	.365	-.896
	15	No	3.50	.90	-.174	-.394
Applied learning	15	Yes	3.87	.93	.099	-1.689
	15	No	3.30	1.02	-.209	-.201
Career Barriers						
Lack of confidence	15	Yes	2.00	.78	.377	-.991
	10	No	2.38	.94	-.920	-.920
Inadequate preparation	15	Yes	2.38	.79	-.435	-.199
	10	No	2.30	.74	-.834	-.651
Decision-making difficulties	15	Yes	1.77	.98	1.590	2.064
	15	No	2.21	.97	.446	-.638
Dissatisfaction with career	15	Yes	1.83	.83	1.049	.713
	15	No	1.91	.78	.071	-1.494
Job market constraints	15	Yes	1.73	.92	1.494	1.405
	15	No	2.35	.94	-.249	-1.081
Difficulty with networking	15	Yes	1.83	.82	1.13	.966
	15	No	2.37	1.14	.408	-.795
Overall GPA	15	Yes	3.15	.50	-.691	-.904
	15	No	3.27	.51	-.838	-.160

Power Analysis and Sample Size Test

The result of power analysis indicated that sample size = 64 could reach the power .9.

Multivariate Analysis of Variance (MANOVA)

A MANOVA was used to examine research hypotheses 2-5. Researchers used SPSS Version 22 and SAS Software were used to perform analyses. The first step in accomplishing MANOVA is to test the homogeneity of covariance. The Box's Test of Equality of Covariance

Matrices (Box's M) is used to determine homogeneity of covariance for checking the serious violations of the assumption of homogeneity of variances and covariance across groups. The Box's M with a significance score of $p < .05$ increases the risk of a Type I error and reduces statistical power particularly when any group's sample size is small or extremely unequal among groups. Unless the sample sizes are unequal, it may ignore it; otherwise, the test is not robust (Tabachnick & Fidell, 2001). In the current study, none of the Box's M tests were significant, so there were no serious violations of the assumption of homogeneity of variances and covariance across groups.

The second hypothesis examining whether taking CTE and utilizing career service impact on students' career development in STEM higher education. The MANOVA revealed that there was no main effect between CTE and non-CTE groups, but there was main effect between career service (mean=4.03) and non-career service (mean = 3.60) groups in the career management domain. Wilks' lambda is .923, $F(1, 143) = 2.917$, $p\ (.024) < \alpha\ (.05)$, partial $\eta 2 = .077$. Thus, the null hypothesis that students utilized career service significantly impact on their career management. The results of MANOVA were shown in Table 27 and Figure 5.

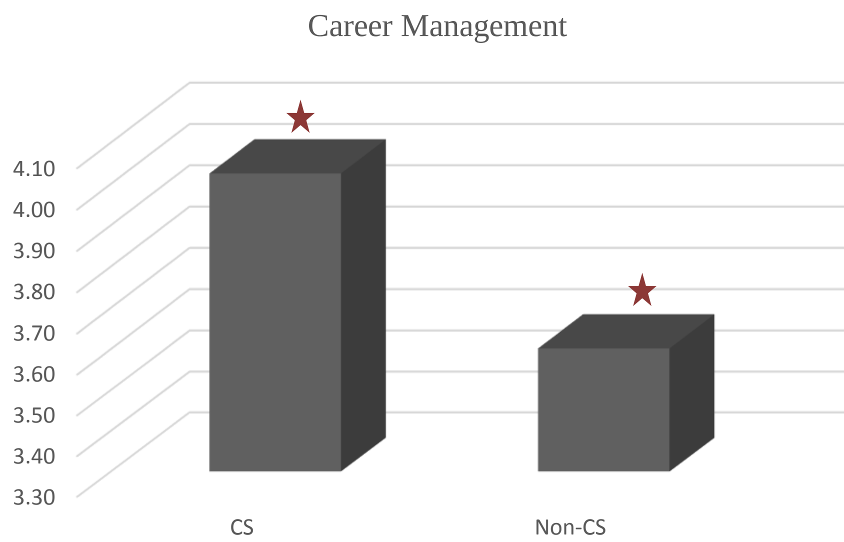


Figure 5. Utilized career service impact on career management.
✱ *p*<.05.

Hypothesis 3 tested whether different STEM majors impacted students career development and the results indicated that the Box's M test (p = .464) was not significant. The MANOVA revealed that there was a significant main effect between majors in the work-based learning and the career management domains. Wilks' lambda is .757, F (3,140) = 7.98, p (.005) < α (.05), partial η2 = .089. Specifically using Post Hoc-LSD test, students that majored in science (mean=3.35) had higher scores in work-based learning than students that majored in engineering (mean=2.77) and mathematics (mean=2.51). Students that majored in engineering (mean = 3.94) had higher scores in career management than students that majored in mathematics (mean = 3.25). The results of MANOVA were shown in Table 27 and Figures 6, 7.

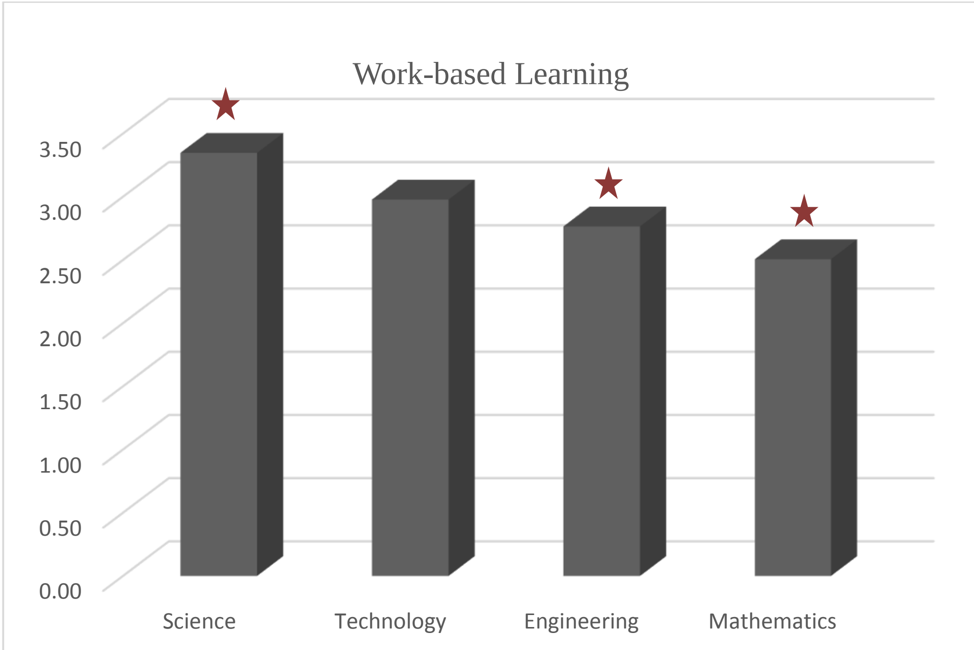


Figure 6. Different STEM majors impact on Work-based Learning
* *p*<.05.

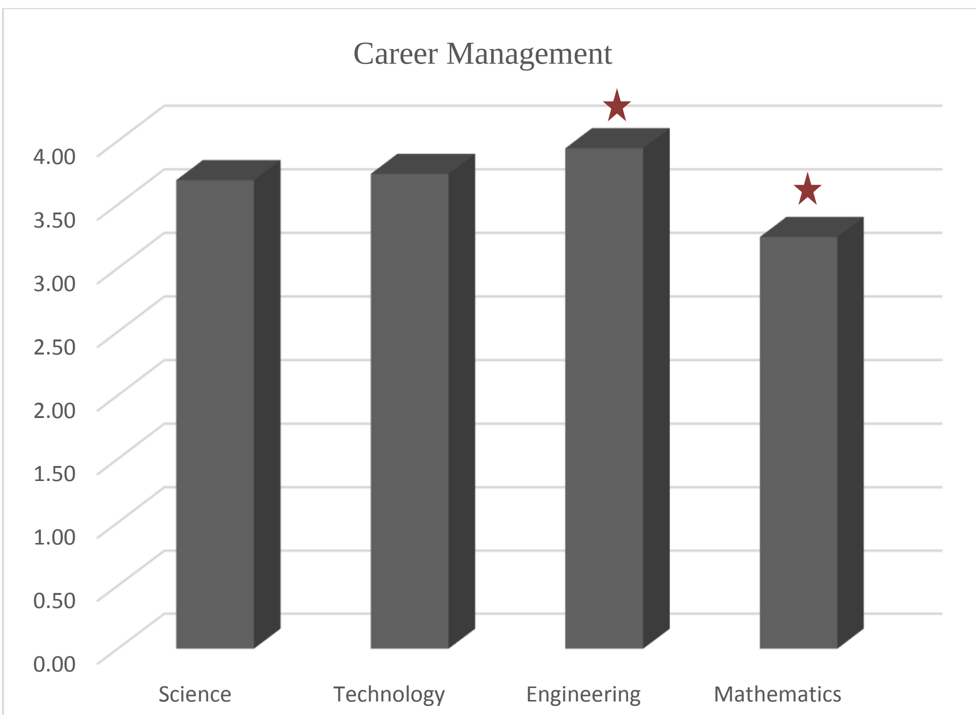


Figure 7. Different STEM majors impact on career management
* *p*<.05.

Finally, there was no main effect between the full-time employed and non-full-time employed groups in career barriers but career development. The MANOVA revealed that new STEM graduates who were individuals employed full-time in STEM had higher scores in skill development, work-based learning, and career management in college. Wilks' lambda is .616, F (4, 25) = 3.890, *p* (.014) < α (.05), partial η2 = .384. Thus, the null hypothesis that individuals employed full-time in STEM had better career development in STEM higher education was supported. The results of MANOVA were shown in Table 27 and Figures 8, 9, and 10.

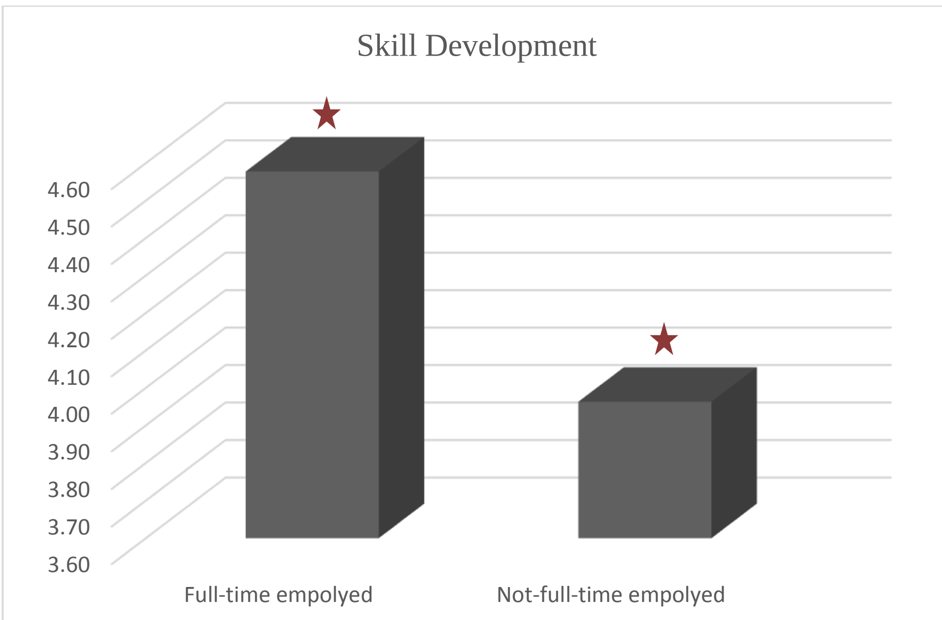


Figure 8. New graduates' empolyment status associated with their skill devleopment in college. ✱ *p*<.05.

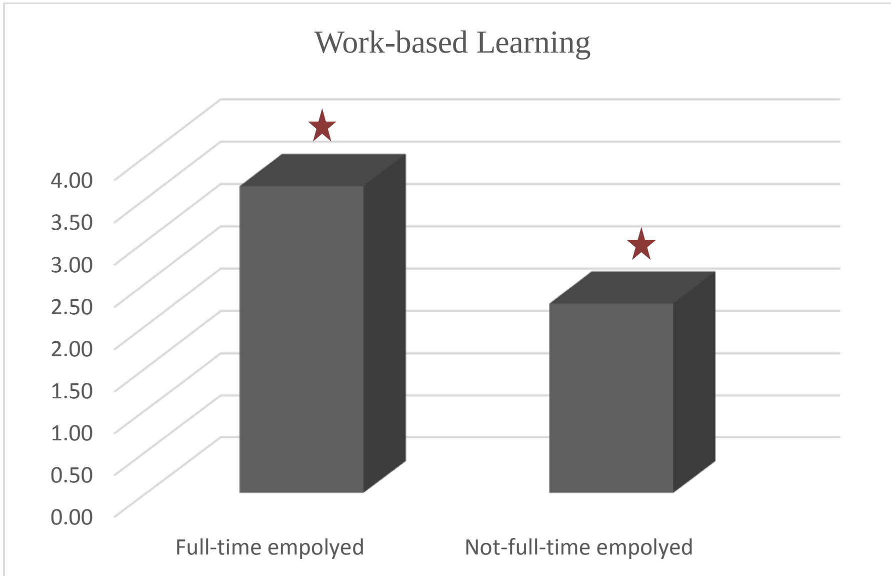


Figure 9. New graduates' empolyment status associated with their Work-based Learning in college. *p*<.05. ★

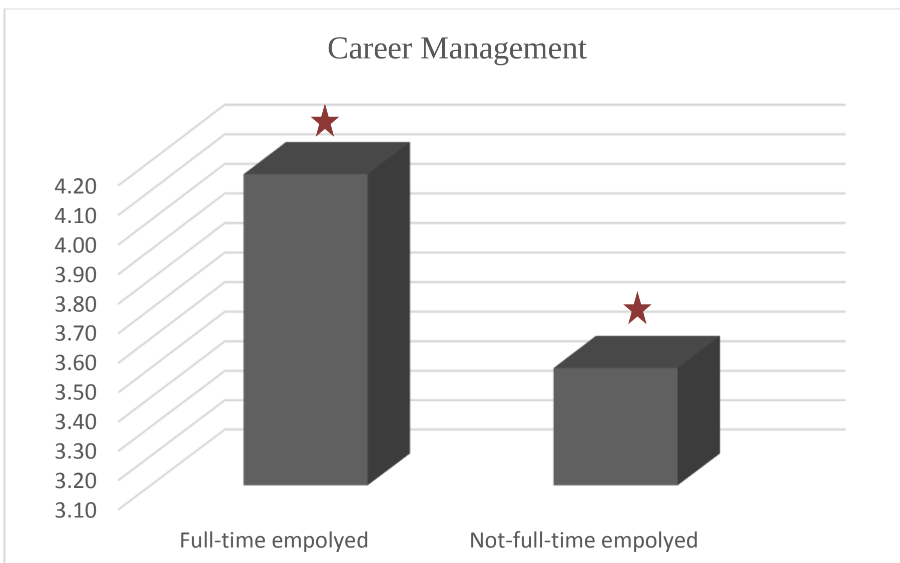


Figure 10. New graduates' empolyment status associated with their career management in college. ★ *p*<.05.

Table 27

MANOVA Results

No.	Effect	Outcome Variables	Wilks' Lambda	F	Sig	Partial Eta Squared	Observed Power[e]
H2	Career Service	Career Development					
		Skill Development	.923	2.943	.088	.020	.399
		Work-based Learning	.923	.0120	.913	.000	.051
		Career Management	.923	7.980	.005*	.053	.801
		Applied Learning	.923	3.129	.079	.021	.420
H3	STEM Majors	Career Development					
		Skill Development	.757	1.096	.353	.023	.291
		Work-based Learning	.757	2.888	.038*	.058	.679
		Career Management	.757	3.346	.021*	.067	.750
		Applied Learning	.757	1.699	.170	.035	.437
H4	Employment Status	Career Development					
		Skill Development	.616	7.103	.013*	.202	.730
		Work-based Learning	.616	12.566	.001*	.310	.928
		Career Management	.616	5.711	.024*	.169	.636
		Applied Learning	.616	2.532	.123	.083	.336

* $p<.05$

Second, logistic regression analysis is used when the dependent variable is a categorical variable. In this section, researchers focused on building a model predicting new STEM graduates' employment status (1: fully time employed; 0: under-un-employed) based on their career development in the college.

Logistic Regression Analysis

Normality Analysis

The assumptions of the general liner model are included in a multivariate normal distribution for both independent and dependent variables, linear relationship between predictors and the outcome variable, and homogeneity of element of the variance/covariance matrix for the predictors across all groups (Warner, 2008). Unlike the general liner model assumptions, the assumption of performing binary logistic regression analysis is less restrictive. The outcome variable is dichotomous, and scores on the outcome variable must be statistically independent of each other. In other words, logistic regression analysis is not required to test the normality of variables (Wright 1995; Warner, 2008).

Logistic Regression Analysis

A binary logistic regression analysis was conducted to test students' career development (i.e. skill development, work-based learning, career management, and applied learning) in predicting participant's employment status in the STEM workforce. The outcome variable, employment status, was categorized into full-time employed and not full-time employed (i.e. unemployed or underemployed) in the STEM workforce.

The results indicated that students' career development in STEM higher education significantly predicted their employment status in the STEM workforce. The overall model containing student's skill development (SD), work-based learning (WB), career management

(CM), and applied learning (AL) was significant (likelihood ration and Score, *p* <.05). Specifically, students' work-based learning positively predicted their employment status (*p* <.05). The model as a whole explained between 40 % (Cox and Snell *R* square) and 53.3 % (Nagelkerke R squared) of the variance of new graduates' employment status and correctly predicts 86.2% (the concord statistic score) of new graduates' employment status.

$$\log\left(\frac{p}{1-p}\right) = -.9.97 + 2.09\ X_{SD} + 1.25\ X_{WB} -.35\ X_{CM} -.34\ X_{AL}$$

The results of the logistic regression contained in Table 28, shows only career development made a significant contribution to the employment status model with an odd ratio of 1.315 for every unit increase in the work-based learning score.

Table 28

Logistic Regression Analysis on New STEM Graduates' Employment Status by the Predictors

	β	SE	Wald Chi-Square	Odds Ration	*p*	95% CI
Intercept	-9.97	4.99	3.999	*	.0046	*
Career Development						
Skill Development	2.09	1.35	2.411	.124	.1205	.009-1.730
Work-based Learning	1.25	.62	4.090	.288	.043*	.086-.962
Career Management	-.35	1.13	.094	1.414	.759	.154-12.957
Applied Learning	-.34	.71	.232	1.406	.629	.353-5.606

* *p*<.05

Multiple Linear Regression Analysis

Third, multiple linear regression was used to test whether students' career development predicting their GPA in hypothesis 7. Prior to perform GLM, all variables were tested normality of distribution, linearity, the reliability of measurement, and homoscedasticity.

Normality Analysis

Normality tests for both career development and career barrier assessments were indicated that the data were seen normally distributed except the skill development sub-scale.

Power Analysis and Sample Size Test

In the current study, there were 145 samples which only reach the power .701.

Multiple Linear Regression Analysis

To test whether students' career development in STEM higher education predict their GPA, a generalized linear regression analysis was used to test hypothesis 7. First, stepwise multiple linear regression analysis was conducted to assess the degree of students' skill development, work-based learning, career management, and applied learning predicting their GPAs in STEM higher education. Gender and majors were included in the model as control variables. The overall regression predicted student's GPA from career development which is F (8, 133) =2.01, p=.05, about 5.4 % of the variance in students' GPA could be predicted (R=.329, R^2=.108, and R^2_{adj} = .054). Specifically, Skill Development (r=.272, p=.015) was the significant predictor of students' GPA when the variables of gender and majors were statistically controlled. Researchers tested the validity of model using MCMC simulation methods. The results are similar to the one reported above obtain from SAS®. The result was shown in Table 29, and the equation was:

$$Y_{GPA} = 2.491 + .272X_{SD} - .029X_{WB} - .014X_{CM} - .101X_{AP} + \varepsilon_i$$

In Table 30, researchers summarized each hypothesis with its corresponding the method of data analysis and the result.

Table 29

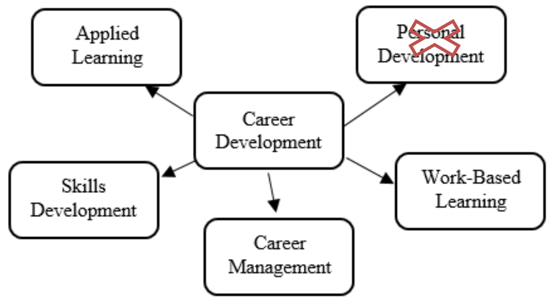
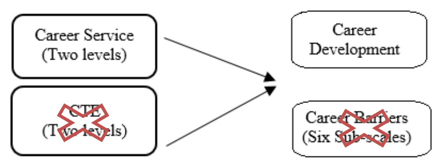
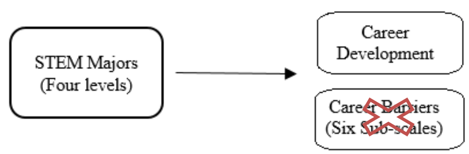
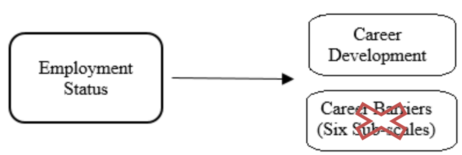
Students' Career Development Predict GPA

	Variable	GPA		
		β	R^2_{change}	VIF
STEP 1	Gender	.141		1.220
	Major_1_Dummy Coding	-.165		1.520
	Major_2_Dummy Coding	-.122		1.393
	Major_3_Dummy Coding	.041	.059	1.400
STEP 2	Skill Development	.272*		1.806
	Work-based Learning	-.029		1.499
	Career Management	-.014		2.068
	Applied Learning	-.101	.049	1.669
				Intercept =2.491
				R =.329
				R^2 =.108*
				R^2_{adj}=.054*

Note. *p<.05, **p<.001

Table 30

The Results of All Data Analyses

No.	Hypothesis	Diagram	Data Analysis	Results
1.	Student's career development consists of five factors including personal development, applied learning, skill development, work-based learning, and career management.		Exploratory Factor Analysis	Four Factors with total 33 questioners.
2.	Students that utilized career services and took CTE courses have higher levels of career development and lower levels of career barriers.		Multivariate Analysis of Variance (MANOVA)	Main effect in career management between CS and non-CS groups.
3.	Students with different STEM majors have different levels of career development.		Multivariate Analysis of Variance (MANOVA)	Main effect in WB and CM between STEM majors.
4.	Individuals employed full-time in STEM have higher levels of career development and lower levels of career barriers.		Multivariate Analysis of Variance (MANOVA)	Main effect in SD, WB, and CM between full-time and non-full-time.

Note: the result does not support the hypothesis.

Table 30

The Results of All Data Analyses (continued)

No.	Hypothesis	Diagram	Data Analysis	Results
5.	Student's career development in STEM higher education will predict their career barriers in STEM workforce	Employment Status → Career Barriers (Six Sub-scales)	Multivariate Analysis of Variance (MANOVA)	No main effect
6.	Student's career development in STEM higher education will predict their employment status.	Career Development → Employment Status	Logistical Regression	Students' career development predicts their employment status (WB was the significant predictor)
7.	Student's career development in STEM higher education will predict their GPA	Career Development → GPA (Control gender and majors)	Generalized Linear Model **(**GLM)	Students' career development predicts their GPA (SD was the significant predictor)

Note: the result does not support the hypothesis.

CHAPTER 5

DISCUSSION AND CONCLUSIONS

In chapters 1 through 4, researchers identified the research questions, developed the hypotheses to be tested, defined the scope of variables, designed the research methods, and performed data analyses to test the hypotheses. The purpose of this chapter is to provide an overview, discussions, implications, conclusion, and future directions of the study.

Developing Career Development Assessment

In the current study, researchers hypothesized that student's career development consists with five factors (Rae, 2007) including personal development, applied learning, skill development, work-based learning, and career management. Based on the results from performing exploratory factor analysis, students' career development consists with four factors: skill development, work-based learning, career management, and applied learning. The total 58 items of assessment were modified to 33 items. The personal development domain was not included in the final career development model. Researchers carefully reviewed all seven items of personal development domain. They found that personal development items are related to Skills Development, Work-based learning, Career Management, and Applied Learning domains. For instance, one of Personal Development question will ask the degree of students' department or college gave them support and encouragement to produce useful documents (i.e., resume, curriculum vitae or job application) to meet employer criteria or their career plan. This question is similar to the questions assessing student's' career manage domain. Another example, Personal Development will ask the degree of students' department or college gave them support and encouragement to make connections between theoretical, practical application, and fact-based learning. It is also similar to assess students' applied learning domain. The implication of developing the career development assessment is that Personal Development is redundant in this survey. The Skills Development, Work-based Learning, Career Management, and Applied Learning domains are able to assess students' career development in the current study. Although, personal domain is not included in the model, researchers suggested that the need of collecting more data from different populations in the future.

CTE and Career Development

In the second hypothesis, researchers hypothesized that students taking CTE in high school should have higher levels of career development and lower levels of career barriers. The results indicate that CTE does not have a main effect to either students' career development or career barriers in this study. In other word, students taking or not taking CTE courses did not impact their career development in STEM higher education and career barriers in the workforce. The results from current study are contradict with previous studies. Therefore, there is need of extending study to clarify the confusions in the current study. Researchers suggested that the percentage of students reported they ever taking CTE (11.7%) was too low in the current study. According to a report from Associated for Career & Technical Education (ACTE), it indicates 94 percent of all high school students ever taking CTE in high school. Although the ACTE report indicates that students with lower income, rural schools, disabilities, lower academic achievement were more likely to participate in secondary CTE at higher levels (ACTE, 2006). Researchers suggested the overall percentage of students taking CTE in the current study was too low in this study. Researches reviewed the survey, and they found the problem may due to the survey question (i.e. did you take CTE classes in high school or community college?) over simplified which may cause students did not answer the question correctly. In the question, it does not provide enough information and definition for CTE which may not help students to recognize their experiences of taking CTE in high school. In the future study, researchers suggested to provide full explanation what CTE is in the demographic questionnaire for getting students' right answers regarding their experiences of taking CTE.

Career Service and Career Development

Researchers hypothesized that students utilizing career service in college should have higher levels of career development and lower levels of career barriers. The results indicate that students utilizing career services in college have higher levels of career management. The purpose of career services is mainly focused on preparing students for their job search, making of their resume, and career guidance. The results of the current study showed a significant difference in the career management domain between the CS and non-CS groups, indicating the importance of career services in obtaining STEM employment. Previous studies support similar benefits of career services for students' career search and career decision-making during college (Gati, Krausz, & Osipow, 1996; Lancaster, Rudolph, Perkins, & Patten, 1999; Fouad, Guillen, Harris-Hodge, Henry, Novakovic, Terry, & Kantamneni, 2006). In term of career barriers; however, students utilizing career service was not associated with levels of career barriers. In other word, students utilizing career service in college is not associated with their career barriers in workforce which is not consistent with previous studies. The implication of current study is to provide evidence that career services could support students' career management in STEM higher education. Although, career service in college is very useful for students' career development, only about 37% of students ever utilized career service in the current study, researchers suggested that there is the need of encouraging more students to attend career service in college.

Career Development in Different STEM Majors

The purpose of comparing students' career development between science, technology, engineering, and mathematics majors in the current study was (1) to test whether different majors may emphasize on career development differently, and (2) to evaluate how to improve student's career development by STEM majors. Previously, there is no study direly integrating enterprise, employability and curriculum concepts to assess students' perspectives regarding their degree programs how to support their career development among specially among science, technology, engineering, and mathematics majors. In the current study, the results indicate students' career developments significantly different among science, technology, engineering, and mathematics in this school. Students majored in sciences had higher scores on Work-based Learning development than students majored in engineering and mathematics, and students majored in engineering had higher scores on Career Management development than students majored in mathematics. Furthermore, new graduates' career barriers are not associated with different majors in the current study. The implication of current study is to provide educators and researchers beware of students' career development among different majors.

Employment and Career Development

Comparing full-time and non-full-time (i.e. under employed, unemployed) new graduates their career development experiences in college, the results indicate that individuals employed full-time in STEM had higher scores on Skill Development, Work-based Learning, and Career Management in college. Using students' career development to predict their employment in the workforce, the results showed that students' Work-based Learning in college was the significant predictor for whether full-time or non-full time employed in STEM workforce later on.

Previous study suggested those college students' capabilities in career management impact on their employability, graduate job attainment, and long-term career success. Therefore, supporting students' career management competencies could strengthen new graduates' employee mobility, career pathways, and industry partners. Meanwhile, student's career management is also associated with their work-integrated learning (Jackson & Wilton, 2016). In term of new graduates' career barriers and employment status, again there were associated in the current study. Based on the career development model, it provides educators and researchers to predict whether students could successfully transit from college to industry in STEM fields. The implication of current study is that the model could be used to evaluate and improve a degree program of supporting students' development based new graduates' employment status.

Academic Performance and Career Development

A previous study comparing two groups of undergraduate students who completed (n=3,546) and did not completed a career development course (n=3,510), researchers concluded that the career development course did significantly predict cumulative GPA. In other words, students who utilized career development course graduated with higher GPAs (Hansen, Jackson, & Pedersen, 2017). Similar to the results from the current study, student' Skill Development significantly predicted their GPA. Students' Skill Development was a significant predictor of students' GPA. Career barriers again were not associated with student's GPA. The implication is to provide educators and researchers models to predict whether students could successfully transit from college to industry in STEM fields, and an indicator to evaluate their degree program how to improve for closing the skills gap between higher education and workforce demands.

Future Directions

Based on the results of the current study, it suggests that there is the need of integrating employability and enterprise into curriculum design for preparing students' career development and employability in STEM higher education. Students' Skill Development, Work-based learning, Career Management, and Applied learning domains were associated with their GPA in college, their employment status in STEM workforce. Career Services in college plays one part of preparing students' career management in the current study. Although Career Barriers Inventory Revised (CBI-R; Swason, Daniels & Tokar, 1996) have well accepted for assessing individual' carriers barriers, the results showed that new graduate's (1) lack of confidence, (b) inadequate preparation, (c) decision-making difficulties, (d) dissatisfaction with career, (e) job market constraints, and (f) difficulties with networking or socialization domains not associated with any variables including Career Development, CTE, CS, employment, and GPA in current study. Researchers provided some suggestions to increase the validation of the assessment and models in the current study: (1) conducting a longitudinal study as Table 31, (2) collecting more cross-sectional data from different universities and populations as Table 31, (3) performing confirmatory factor analysis and structural equation modeling analysis to explain the relationships among Skill Development, Work-based learning, Career Management, and Applied Learning domains of the theory, and (4) conducing experimental designs for testing the cause and effect relationships between students' career development, employment status, and GPAs. Finally, researchers suggested that the career development assessment is required constantly to update based on the trends of workforce development and the trends of new teaching and learning. The assessment could provide educators to evaluate their curriculum design and increase students’ employability for closing the skills gap and increasing the number of qualified new graduates in STEM fields.

Table 31

Cross-sectional and Longitudinal Data Collection Processes

Data Source	**Time 1**		**Time 2**	
Cross-sectional Longitudinal Data	Spring 2017		Fall 2017	
	Participants A	Senior Students	Participants A	New Graduates
	Assessments	1. Demographic 2. Career Development	Assessments	3. Career barriers 4. Employment Status
Cross-sectional Data	Spring 2017			
	Participants B	New Graduates		
	Assessments	1. Demographic 2. Career Development 3. Career Barriers 4. Employment Status		
Cross-sectional Data (from other colleges)	Fall 2017			
	Participants C, D	New Graduates		
	Assessments	1. Demographic 2. Career Development 3. Career Barriers 4. Employment Status		

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APPENDIX A

HUMAN SUBJECTS INFORMED CONSENT

You are invited to participate in a study assessing the various factors for predicting new graduates' employability and career barriers in workforce.

DESCRIPTION OF THE STUDY AND INTERVIEW

In the survey, you will be asked several questions regarding your experiences of career development in your college or program department. The entire survey will take you about 30 minutes. To receive the full extra credit, you must finish all survey questions.

(For longitudinal study only)

You will also be asked to participate in an additional fifteen-minute survey held approximately 6 months following your graduation. This portion of the study is not linked to your extra credit, but you will be offered a 10-dollars gift for compensation. You will be asked your employability status and career barriers in workforce.

BENEFITS

By participating in this study, you are helping to build a survey and models which could provide educators and policy-makers with a tool to estimate and assess policies and strategies for increasing employability and decreasing career barriers in STEM workforce.

CONFIDENTIALITY

All the information and survey questions collected during this study will be kept confidential. Your personal responses will not be shared with anyone and your name will not be associated with your responses. All the data collected in this study will be stored on a password-protected computer and will be accessible only to the study investigators. The results of this research may be reported in academic papers and presented at national conferences. Your individual responses will be kept confidential and will not be reported in any way that identified you.

CONTACT

If you have questions about the study or the procedures, you may contact the study investigators:

Ginger S. Watson, Ph.D., Responsible Project Investigator
Old Dominion University, STEM Education & Professional Studies Dept. Darden College of Education, Phone: 757-683-3246
Email: gswatson@odu.edu

Yi-Ching Lin, Researcher
Old Dominion University, STEM Education & Professional Studies Dept. Darden College of Education, Phone: 804-490-5426
Email: yxlin001@odu.edu

If you feel have not been treated according to the descriptions provided, or your rights as a participant in researcher have not been honored during this study, you may contact Dr. Petros Katsioloudis, Chair of Darden College of Education Human Subjects Committee, at pkatsiol@odu.edu.

PARTICIPATION

Your participation in this study is voluntary, so you are free to withdrew your consent to participant and may discontinue your participation at any time. If you withdraw from the study before data collection is completed your data will be securely erased from all storage devices where it resides.

APPENDIX B

INVITATION TO PARTICIPANTS (TEACHER)

I am conducting a study as part of my dissertation assessing undergraduate, **senior students' career development** in science, technology, engineering, and mathematics (STEM). My advisor and I are asking for your assistance in recruiting students from your current 400-level class to complete a 10-15 minute, online survey as part of this study. This study could provide educators and policy-makers with a tool to estimate and assess policies and strategies for increasing employability in STEM.

Please let us know if you are willing to advertise this opportunity to students in your class(es) and we will provide you with recruitment information, including the survey link, that may be posted to Blackboard or sent directly to students via e-mail.

Also let us know if you are willing to offer students extra credits (any type) to encourage participation. We will provide you with a list of students who completed the survey in your class by the second week of April (when the study closes).

This protocol has been approved by the Darden College of Education Human Subjects Committee. The IRB approval letter is attached as a reference.

We really appreciate your help.

Sincerely,

Yi-Ching Lin, Researcher
Old Dominion University, STEM Education & Professional Studies Dept. Darden College of Education, Phone: 804-490-5426, Email: yxlin001@odu.edu

Ginger S. Watson, Ph.D., Responsible Project Investigator, Old Dominion University, STEM Education & Professional Studies Dept. Darden College of Education, Phone: 757-683-3246, Email: gswatson@odu.edu

APPENDIX C

INVITATION TO PARTICIPANTS (STUDENT)

You have been selected to participate in a research study assessing Career development of new Science, Technology, Engineering, and Mathematics (STEM) graduates at ODU. Your participation will involve completing a 15-20 minute, online survey. You will receive a $20 Amazon gift card to compensate for your time.

BENEFITS

There are no direct benefits to you for participating in this study. By participating in this study, you are helping us develop a tool to increase employability of new graduates. Your participation is important to us.

CONFIDENTIALITY

Your personal information and individual responses collected during this study will be kept confidential and will be accessible only to the researchers listed below. Results will be reported in a way that does not personally identify you.

CONTACT

If you have questions about the study or the procedures, you may contact the study investigators:

Yi-Ching Lin, Researcher Old Dominion University, STEM Education & Professional Studies Dept. Darden College of Education, Phone: 804-490-5426, Email: yxlin001@odu.edu

Ginger S. Watson, Ph.D., Responsible Project Investigator, Old Dominion University, STEM Education & Professional Studies Dept. Darden College of Education, Phone: 757-683-3246, Email: gswatson@odu.edu

If you feel have not been treated according to the descriptions provided, or your rights as a participant in researcher have not been honored during this study, you may contact Dr. Petros Katsioloudis, Chair of Darden College of Education Human Subjects Committee, at pkatsiol@odu.edu.

APPENDIX D

DEMOGRAPHIC QUESTIONNAIRE

1. Gender:

☐ Male

☐ Female

☐ Prefer not to answer

2. Age: ________

3. What was your major(s) in college?

4. Career Choice Status:

☐ I am undecided about a career

☐ I am tentatively decided about my career

☐ I have decided on a career

5. List the future career choices you are considering: 1st Choice:

6. List the future career choices you are considering: 2nd Choice (if applicable)

7. Race/Ethnicity (Choose all that apply):

☐ African-American/Black

☐ Asian-American/Asian

☐ Hawaiian/Pacific Islander

☐ European-American/White

☐ Hispanic-American/Latino

☐ Native American

☐ Other:

8. Are you a native speaker?

□ Yes

□ No

9. Did you take CTE (Career and Technical Education) classes in high school or community college?

□ Yes, please list the courses you have taken. ______________________________

□ No

10. Have you even attended any major/career service offered by the university? Such as CME (center for major exploration)/CDC (career development service)?

□ Yes

□ No

11. Are you former military or a veteran?

□ Yes

□ No

12. Are you currently in enrolled in graduate school?

□ Yes, what program are you studying? ________________________

□ No

13. What is your overall GPA? __________

14. What is your major GPA? ________________

(If you graduated, what is your final major GPA)? __________

15. My current employment status

 I am a full-time employee working 40 hours per week and the job is related to my major.

 I am a full-time employee working 40 hours per week and the job is not related to my major.

 I am a part-time employee working less than 40 hours per week and the job is related to my major.

 I am a part-time employee working less than 40 hours per week and the job is not related to my major.

 I am self-employed, and the job is related to my major.

 I am self-employed, and the job is not related to my major.

 I am still looking for jobs.

 I am a graduate student.

APPENDIX E

CAREER DEVELOPMENT QUESTIONNAIRE

Circle the number that best describes you or the experiences you have had in your department (major program of study) or college.

Strongly Disagree	Disagree	Neither Agree Nor Disagree	Agree	Strongly Agree
1	**2**	**3**	**4**	**5**

Personal Development

My department or college gave me support and encouragement to:

1.	…set my personal learning goals (courses I need to take, skill and knowledge I need to develop) to reach my career goal.	1 2 3 4 5
2.	…reflect my personal learning and skills development related to my career goal.	1 2 3 4 5
3.	…produce useful documents (i.e., resume, curriculum vitae or job application) to meet employer criteria or my career plan.	1 2 3 4 5
4.	…assess my personal learning and skills development for evidence of attainment.	1 2 3 4 5
5.	...make connections between theoretical, practical application, and fact-based learning.	1 2 3 4 5
6.	...apply theoretical knowledge in practice.	1 2 3 4 5
7.	…transfer knowledge and skills between school and the workplace.	1 2 3 4 5

Applied Learning

My department or college provided me with:

8.	...work-based projects or assignments to show evidence of applied learning.	1 2 3 4 5
9.	…work-based projects or assignments to transfer skills from academia to the workforce.	1 2 3 4 5

10.	…opportunities to speak with employers and organizations related to my degree program.	1 2 3 4 5
11.	...presentations from guest speakers in industries related to my degree program.	1 2 3 4 5
12.	...participation in live case studies (i.e., hands-on experience applying theories and models to meet real requirements in workplace environment).	1 2 3 4 5
13.	…interactive and simulation-based learning activities mimicking workplace environments.	1 2 3 4 5

Skills Development

My department or college gave me support and encouragement to develop the skill of

14.	...self-organization	1 2 3 4 5
15.	...time management	1 2 3 4 5
16.	…budgeting	1 2 3 4 5
17.	…finding opportunities(internship, service etc.) for my professional and career development	1 2 3 4 5
18.	…taking the initiative to act on opportunities	1 2 3 4 5
19.	…creative thinking	1 2 3 4 5
20.	…problem solving	1 2 3 4 5
21.	…verbal communication	1 2 3 4 5
22.	…written communication	1 2 3 4 5
23.	…interpersonal relationship building	1 2 3 4 5
24.	…negotiation	1 2 3 4 5
25.	...persuasion	1 2 3 4 5
26.	…leadership	1 2 3 4 5
27.	…project management	1 2 3 4 5

28.	…numerical, analytical, and quantitative analysis	1 2 3 4 5
29.	...computer skills related to my career goal	1 2 3 4 5
30.	...professionalism	1 2 3 4 5

My major or college enabled me to:

31.	...make plans	1 2 3 4 5
32.	…set goals	1 2 3 4 5
33.	…achieve goals	1 2 3 4 5
34.	…make decisions	1 2 3 4 5
35.	...accept risks in conditions of uncertainty	1 2 3 4 5
36.	…work independently	1 2 3 4 5
37.	...take responsibility for achieving results	1 2 3 4 5
38.	…apply academic learning in the workplace	1 2 3 4 5
39.	…adapt and work flexibly in different contexts	1 2 3 4 5
40.	..participate in social and industry or professional networks	1 2 3 4 5
41.	...work effectively as part of a team to achieve results	1 2 3 4 5
42.	…take responsibility for meeting quality standards	1 2 3 4 5

My major, college or university increased:

43.	…my self-confidence	1 2 3 4 5
44.	...my self-efficacy (a belief in my ability to execute the behaviors necessary to achieve my career goal)	1 2 3 4 5

Work Based Learning

My major or college provided me with a:

45.	…short-term work experience placement of couple weeks.	1 2 3 4 5

46.	…full academic year of work experience placement.	1 2 3 4 5
47.	…relevant part-time, casual, or vacation work.	1 2 3 4 5
48.	…voluntary, community, or social enterprise work activity.	1 2 3 4 5
49.	...self-employment or freelancing training.	1 2 3 4 5
50.	…leadership or organization of student clubs, sports activities, or societies.	1 2 3 4 5

Career Management

My major or college provided training on:

51.	...resume or curriculum vitae (another type of resume) preparation.	1 2 3 4 5
52.	…job searching.	1 2 3 4 5
53.	…self-professional skills.	1 2 3 4 5
54.	…communication skills.	1 2 3 4 5
55.	...career guidance.	1 2 3 4 5
56.	…access to industry, vocational, or professional practitioner input (e.g. guest speakers and mentoring).	1 2 3 4 5
57.	...access to professional career events.	1 2 3 4 5
58.	…access to professional career networks.	1 2 3 4 5

APPENDIX F

CAREER BARRIERS ASSESSMENTS (ALUMNI ONLY)

Circle the number that corresponds to how you feel/think now.

Strongly Disagree	Disagree	Neither Agree Nor Disagree	Agree	Strongly Agree
1	**2**	**3**	**4**	**5**

1.	Unsure of my career goals	1 2 3 4 5
2.	Changing my mind again and again about my career plans	1 2 3 4 5
3.	Unsure of how to "sell myself" to an employer	1 2 3 4 5
4.	Becoming bored with my job /career	1 2 3 4 5
5.	Unsure of my work- related values	1 2 3 4 5
6.	Difficulty in finding a job due to a tight job market	1 2 3 4 5
7.	Not feeling confident about my ability on the job	1 2 3 4 5
8.	Not wanting to relocate for my job/career	1 2 3 4 5
9.	Being undecided about what job/career I would like	1 2 3 4 5
10.	Lacking the required personality traits for nay job (e.g. assertiveness)	1 2 3 4 5
11.	Disappointed in my career progress (e.g., not receiving promotions as often as I would like)	1 2 3 4 5
12.	Losing interest in nay job/career	1 2 3 4 5
13.	Difficulty planning my career due to changes in the economy	1 2 3 4 5
14.	Lacking the required skills for my job (e.g., communication, leadership, decision-making)	1 2 3 4 5

15.	Not being sure how to choose a career direction	1 2 3 4 5
16.	Unsure of what my career alternatives are	1 2 3 4 5
17.	Lack of maturity interferes with my career	1 2 3 4 5
18.	Not having a role model or mentor at work	1 2 3 4 5
19.	Having low self-esteem	1 2 3 4 5
20.	No opportunities for advancement in my career	1 2 3 4 5
21.	My belief that certain careers are not appropriate for me	1 2 3 4 5
22.	Lacking information about possible jobs/careers	1 2 3 4 5
23.	The outlook for future employment in my field is not promising	1 2 3 4 5
24.	Being dissatisfied with my job/career	1 2 3 4 5
25.	Unsure of what I want out of life	1 2 3 4 5
26.	Unsure of how to advance in my career	1 2 3 4 5
27.	Lacking necessary educational background for the job I want	1 2 3 4 5
28.	Not knowing the "right people" to get ahead in my career	1 2 3 4 5
29.	Lacking the necessary hands-on experience for the job I want	1 2 3 4 5
30.	No demand for my area of training/education	1 2 3 4 5
31.	Difficulty in finding a job due to a tight job market.	1 2 3 4 5
32.	Not feeling confident about myself in general	1 2 3 4 5
33.	Unable to deal with physical/emotional demands of my jobs.	1 2 3 4 5

VITA

Yi-Ching Lin

Darden College of Education
Old Dominion University
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Academic Degrees

M.S.	Virginia State University	2012 General Psychology
B.S.	University of Missouri-Columbia	2009 Psychology
B.S.	National Taipei University of Technology	2001 Chemical Engineering

Professional Experience

2014 ~ Present	Iota Lambda Sigma (Professional Society in Workforce Development)
2011 ~ 2012	American Psychological Association
2011	Inducted into the International Honor Society in Psychology
2010 ~ 2012	Member, Society for Research on Child Development

Peer-reviewed & Conference Papers

Lin, Y.C, & Watson, G.S. (2015). Investigating college students majoring in stem: statistical and simulation approaches. 2015 modeling simulation visualization student capstone conference, VMASC, Suffolk, Virginia.

Lin, Y.C, & Watson, G.S. (2014). A pilot study investigating college students majoring in stem a: a system dynamic approach. Modsimworld conference, Hampton, Virginia.

Whitehill, J., Serpell, Z.N., **Lin, Y.C**., Foster, A., & Movellan, J. (2014). The faces of engagement: automatic recognition of student engagement from facial expressions. Affective computing, IEEE transactions on, 5(1), 86-98.

Whitehill, J., Serpell, Z.N., Foster, A., **Lin, Y.C**., Pearson, B., Bartlett, M., & Movellan, J. (2011). Towards an optimal affect-sensitive instructional system of cognitive skills. Computer vision and pattern recognition workshops (CVPRW), 2011 IEEE computer society conference on, 20-25.

Papers in Progress

Crompton, H., **Lin, Y.C.,** Elgaouni, O. & Asija, J.P., (in preparation). Students' engagement, satisfaction, and performance in introductory oceanography class predicting students' choosing geoscience majors and careers in higher education.

Lin, Y.C., Crompton, H., Asija, J.P., & Elgaouni, O. (in preparation). Can social cognitive career theory tell students choosing stem and non-stem in higher education?

Lin, Y.C, Nortey, P.M.W, & Oliver Hill, Jr., & Serpell, Z.N. (in preparation). Family functioning is more important than family structure for African American adolescents' cognitive outcomes. *Journal of marriage and family.*

Lin, Y.C, Serpell, Z.N., & Whitehill, J. (in preparation). Facial and behavioral engagements between face-to-face and online iPad cognitive tutoring. *Computer & education.*

Conference Oral and Poster Presentations

Crompton, H., **Lin, Y. C**., Elgaouni, O., & Asija, J.P. (2017). Educational technologies to support in the teaching and learning of mathematics. National aeronautics and space administration (NASA), Virginia air and space center, Virginia.

Crompton, H., **Lin, Y. C**., Asija, J.P., & Elgaouni, O. (2017). Using Robots to Teach Mathematical Functions: A Mixed Methods Comparative Analysis of Achievement and STEM Perceptions.

Lin, Y.C, Watson, G.S., & Diawara, N. (2017). Does career development in college influence employability in stem? 2014 fourth annual graduate research achievement day in Old Dominion University, Norfolk, Virginia.

Riley, T., **Lin, Y.C**., Swafford, A., Whitehill, J., & Serpell, Z.N. (2016). Physiological indices of emotion regulation and facial affect during a problem-solving task. Poster presented at the all-hands meeting of temporal dynamics of learning center, UCSD, San Diego, California.

Riley, T., Whitehill, J., **Lin, Y.C.,** Swafford, A., Foster, A., Serpell, Z.N. (2015). Associations between heart rate variability, affective engagement and task performance. Poster presented at temporal dynamics of learning center all hands meeting, San Diego, California.

Lin, Y.C, & Watson, G.S. (2014). A framework explaining college student majoring in stem and non-stem. 2014 fourth annual graduate research achievement day in old dominion university, Norfolk, Virginia.

Lin, Y.C, Diallo, Saikou, & Burgin, Stephen (2013). Developing a simulation for college students learning the rate of law in chemistry. 2013 modeling simulation visualization students' capstone conference, VMASC, Suffolk, Virginia.

Tomovic, C. & **Lin, Y.C**. (2013). *Crafting a message to engage the public in discourse, development, and acceptance of environmental resiliency policies that address sea level rise***.** Presentation in the international organization of social sciences and behavioral research conference, Atlantic, NJ.

Lin, Y.C. (2013*). Developing a simulation for college students learning the rate of law in chemistry*. Presentation at students' capstone conference in Virginia modeling, analysis, and simulation center, Suffolk, Virginia.

Lin, Y.C, Serpell, Z.N., Pearson, B., Vixamar-Owens, D., Foster, A., & Hill, o. (2012). *Examining Associations among different family factors and cognitive skills in African American Adolescents*. Poster to be presented at the 2012 SRCD themed meeting: Positive Development of Minority Children. Tampa, Florida.

Lin, Y.C, Serpell, Z.N, Jacob Whitehill, & Tiera Willis (2012). *Associations among students' facial expressions, tutor feedback & student performance during a problem-solving task.* Poster presented at the annual meeting for the association of psychological science, Chicago, Illinois.

Additional Skills & Training Certifications

2017 Modeling and simulation certificate in education and training
2015 Modeling and simulation engineering certificate
2016 Business modeling and simulation certificate