MEASURING MOTIVATION TO PREDICT PERCEIVED SUCCESS IN E-LEARNING COURSES FOR PRE-SERVICE TEACHERS: A PREDICTIVE-CORRELATIONAL STUDY

by

Erin Fleming

Liberty University

A Dissertation Presented in Partial Fulfillment

of the Requirements for the Degree

Doctor of Philosophy

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ABSTRACT

This study examined whether a predictive relationship exists between perceived success in e-learning courses for pre-service teachers and their motivation toward learning at the college level. In this post-pandemic, technology-driven world, e-learning is more prevalent than ever. Understanding who will be successful in these courses is imperative. This study aimed to determine whether perceived success in e-learning courses for pre-service teachers could be predicted by their intrinsic motivation, extrinsic motivation, and amotivation scores. This predictive-correlational study utilized logistic regression to test the predictor variables: intrinsic motivation, extrinsic motivation, amotivation, motivation subsets, gender, age, sex, and program type against the criterion variable: perceived success. The Academic Motivation Scale is the survey instrument used to collect data from a prominent university's 68 undergraduate students participating in an online section of EDUC 201. The Logistic Regression revealed that the subscale Extrinsic Motivation-identified regulation was a significant predictor of perceived success for pre-service teachers in an online course. Still, none of the other predictor variables had a significant relationship. Further research on the subscales of motivation and their relationship to perceived e-learning success is recommended at a larger scale. Additionally, a similar study using an objective post-course success marker is suggested.

Keywords: Self-Determination Theory, Social Cognitive Theory, e-learning, pre-service teacher, motivation, Academic Motivation Scale, extrinsic motivation, intrinsic motivation

Copyright Page (Optional)

Dedication

I dedicate this dissertation to the family that got me through it. Thank you to Carmela Duffy, my Nana, who allowed me to live under her roof rent-free for ten years to pay off my original education loans and continue with this doctorate. I thank her for listening to me talk about my classes and letting me ignore her as I locked myself in my room to work each night. Thank you to my parents for encouraging me to pursue my dreams and always supporting me in everything I do. I also want to thank my friends, coworkers, and family members who had to hear me talk about this endeavor and when I canceled plans to get work done. Lastly, I want to thank my wonderful fiancé Joshua, for insisting on marrying a doctor so that I did not give up as I neared the end. Our future is the biggest motivation of them all.

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I would like to thank God for giving me the gift of intrinsic motivation toward my education, I would not be here without Him. I have been called to be a lifelong learner and encourage lifelong learning to all those who pass through my classroom doors. I am thankful for the Liberty University School of Education faculty who guided me through this journey. I especially want to thank my Chair, Dr. Struble, for helping me navigate the dissertation process, supporting me, and answering all of my panicked emails when we hit road bumps. You always had answers to the tough questions, championed for me, and provided insight and suggestions whenever I felt I was out of options. I also want to thank Dr. Barthlow for her positive encouragement and unmatched expertise in quantitative research. Thank you for serving on my committee. And another thanks to anyone I have worked with the last few years. It truly took a team of kind people to get me to where I am today.

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List of Abbreviations

Educator Preparation Provider (EPP)

Echelle de Motivation en Education (EME),

Extrinsic Motivation (EM)

Institutional Review Board (IRB)

International Society for Technology in Education (ISTE)

Intrinsic Motivation (IM)

Learning Management System (LMS)

Percentage Accuracy Classification (PAC)

Self Determination Theory (SDT)

Social Cognitive Theory (SCT)

Statistical Package for the Social Sciences (SPSS)

Taxonomy of Motivation (TOM)

Theory of Transactional Distance (TTD)

Variance Inflation Factor (VIF)

CHAPTER ONE: INTRODUCTION

Overview

e-Learning opportunities are rising as the university blueprint adjusts to accommodate rising technology. More students are considering taking online college classes because they are impacted by the Covid-19 pandemic or lifestyle choices such as budget, convenience, and flexibility. However, research indicates that some students are better suited for the online platform than others with a few specific predictor variables, including motivation levels, college major, sex, and age. This chapter briefly discusses the background of motivation and e-learning as well as online educator preparation provider programs. Problem and purpose statements are provided as well as an explanation of the significance of the study, the research question, and all relevant definitions.

Background

The online learning industry is projected to pass $370 billion by 2026 (Hanson, 2021). The movement toward e-learning was gaining speed prior to the 2020 Covid-19 pandemic, which forced every college to offer courses remotely by March of that year. After exposure to the online platform, and changes to policy, availability, cost, and lifestyle, post-secondary students have more options than ever. According to Hanson (2021), 33% of post-secondary school administrators indicate that they will continue to offer remote online options for courses even after their campuses return to pre-pandemic operations. This fact confirms the upswing in the e-learning movement.

Unfortunately, another popular trend in higher education predictions is reduced enrollment in colleges and universities due to high costs and changes in the job market (Hanson, 2021). An alternative transformation is that "higher education will be vibrant, thriving, and more important than ever to US social and economic progress" (Saelinger, 2019, p. 12). How will this happen? Saelinger (2019) suggests a combination of changing collegial demographics and a complete digital transformation. One such demographical change is the age range of college students. Once flooded by recent high school graduates, Monoghan (2021) shares that "over one-third of degree-seeking undergraduates are aged 25 and older" (p. 334). The increasing age diversity in both traditional and online undergraduate programs is just one level of change on the horizon of the future of college education.

Historical Context

Historically, the e-learning industry has roots dating back to the 1840s and has undergone many transformations (Lee, 2017). The original wave of distance education consisted of programs that brought learning out of the classroom and attempted to teach the masses from home. Then, with the technological boom of the 1990s and early millennium, the industry saw the second revival of technology-based education due to access to the World Wide Web (Lee, 2017). This second wave rebranded distance learning to e-learning. However, the technology available in the last two decades has catapulted computer education, educational technology, and e-learning into a third wave. From preschool and early interventions to doctoral education, schools at all levels use e-learning systems (Barbour, 2020). Similar to how the 2020 Covid-19 outbreak forced schools to rethink their online course offerings, the silver lining of the pandemic is the growth beyond predictions of the general e-learning field (Duffin, 2020).

The pandemic acts as a dividing line for the discussion of e-learning. Pre-pandemic students saw online universities as a budget option mostly set aside for adult learners or special circumstances (Duffin, 2020; Lee, 2017; Rodrigues et al., 2019). Pandemic learning was moved online out of necessity forcing all current students to switch to the e-learning platform. The state and federal regulations brought on by the Covid-19 pandemic marked a trial period of exposure for all learners (Barrot et al.,2021; Hanson, 2021; Moorehouse, 2020). The pandemic years of online learning were chaotic and unstructured but allowed for experimentation, trial and error, and risk-taking (Howard et al., 2021b). Finally, post-pandemic education shows many new motivations for e-learning (Ashour et al., 2021; Business Insights: Global, 2021).

Yokoyama and Miwa (2020) link goal orientation, the conception of learning, and learning behavior to successful online learning programs. The researchers found that e-learning programs promote adaptivity, flexibility, and personalized performance (Yokoyama & Miwa, 2020). However, e-learning is not without its pitfalls. Barrot et al. (2020) found that undergraduates defined managing a study calendar, weak work ethic, and reduced quality of learning to be the most significant struggles after switching to e-learning during the pandemic. Corpus et al. (2022) credit pandemic-related motivational declines specific to autonomous motives. When students were forced to learn remotely, many defined a lack of motivation and self-regulatory techniques as their primary struggles (Usher et al., 2021). Historically, motivation and quality of learning have been two of the defining roadblocks of e-learning for; however, the third roadblock: digital literacy and internet availability, have declined in prevalence due to successful efforts to bridge the digital divide (Barrot et al., 2021). As students adjust to e-learning and educators begin to perfect the craft, the question remains if motivation and quality of learning will remain roadblocks for much longer.

The International Society for Technology in Education (ISTE) is an organization charged with bridging the digital divide and promoting digital literacy across all learning platforms and levels. The ISTE standards "provide competencies for learning, teaching, and leading in the digital age, providing a comprehensive roadmap for the effective use of technology in schools worldwide” (ISTE, 2021). Additionally, Starkey (2020) defines three digital competencies necessary for all teachers and teacher preparatory programs: generic digital competence, digital teaching competence, and professional digital competence. Teachers need to be confident using technology, comfortable teaching with and through technology, and conducting themselves professionally on a digital platform (Randi & Corno, 2021). One can teach these competencies theoretically; however, the literature suggests that in order to instruct teachers on how to educate in an online or blended environment, those teachers must first have experience learning in that environment (Bustamante, 2020; Dyment & Downing, 2018; Randi & Corno, 2021).

Theoretical Contexts

To be motivated means to “be moved to do something” (Ryan and Deci, 2000, p. 54). Motivation, therefore, is the driving factor behind actions, thoughts, and accomplishments (Deci & Ryan, 1985). Self-determination theory (SDT) suggests that pre-service teachers have high levels of intrinsic motivation and are, therefore, excellent candidates for e-learning environments. Careers in education have many perks, including work-life balance, a rewarding atmosphere, and instilling a passion for learning in their students (Sanderse & Cooke, 2018; McClean et al., 2019). These personal well-being and happiness values fit the characteristics of SDT defined by Deci and Ryan (1985): autonomy, competence, and relatedness. Deci and Ryan (1985) developed SDT when outlining the differences between extrinsic motivation, intrinsic motivation, and amotivation. Their Taxonomy of Motivation (TOM) suggests that a person requires the competencies mentioned above of autonomy, competence, and relatedness to learn, understand, and succeed within a multitude of categories, e-learning included (Deci et al., 1991). Since motivation is one of the main factors affecting the growth and popularity of e-learning, finding candidates with high levels of intrinsic motivation can lead to higher e-learning success rates (Eom, 2019; Mahande & Akram, 2021).

Another theory that supports the practice of e-learning for pre-service teachers is the social cognitive theory (SCT). This primary theory, developed by Bandura (1977), promotes the idea that people learn from watching and imitating others. Since many teachers base their classroom practices on their role models and past teachers, one of the best ways to ensure that teachers know how to meet ISTE standards is to expose them to distance and blended educational opportunities. Teaching effectively with technology in higher education promotes expertise in e-pedagogy, and online teaching strategies (Larbi-Apau et al., 2017).

Furthermore, Larbi-Apau et al., (2017) found that technological competence is required to design interactive engagements, plan, and manage e-learning environments. In fact, Burazer et al. (2021) found that about 83% of pre-service teachers sampled in a Covid-impacted online teacher prep program indicated that their online or blended methods were acceptable if not satisfactory. Basal and Eryilmaz (2020) confirmed that engagement in education courses increased with the aid of educational technologies. Alternatively, research by Baek & Sung (2020) found that the overall technical competence of teachers was relatively low and that current technology education courses require improvement. These studies demonstrate the points Bandura (1977, 1986) highlights regarding the many benefits of modeling in learning, which can transfer to teacher education programs. Finally, the SCT construct of self-efficacy and confidence of educators is also addressed (Lazowski & Hulleman, 2016).

Social Context

Higher education has a long history of both tradition and evolution. While many of the characteristics that define traditional colleges today were developed between 1865 and 1915, the campus experience has evolved since then. Colleges traditionally played an enormous role in social mobility and economic growth, but the United States no longer leads the world in attendance or research (Mintz, 2017). The identity of higher education has always faced challenging times and has had to adapt to the needs of the decade. As new social, cultural, political, intellectual, and economic perspectives impact the status of higher education today, universities must adapt and adjust (Angulo & Schneider, 2017; Sprehe 2021). Declining college enrollments, potential recessions, the overall mental health of the nation, the declining value of a college degree, and the domination of e-learning are once again changing the face of higher education today (Hanson, 2021). The "decline of higher education," as reported by Saelinger (2019) before the pandemic and Gallup-Lumina (2022) afterward, are just the newest predictions in the resilient history of higher education.

The Covid-19 Pandemic of 2020 created a wave in education that will continue to affect the trajectory of e-learning for the remainder of the decade (Barrot et al., 2021; Hanson, 2021; Moorehouse, 2020). The crisis disrupted education and did not come without its struggles and difficulties (Ashour et al., 2021; Johnston et al., 2021). However, it forced an era of trial and error, creativity, and of risk, which resulted in positive changes occurring in its aftermath. Distance and blended learning opportunities may be the thing to save higher education, and the third wave of e-learning will bring new opportunities to a new demographic of students (Howard et al., 2021b). Since motivation is an identified obstacle for e-learning platforms, a better understanding of motivation through SDT and SCT is necessary. Since teachers model their teaching styles based on their learning experiences, a mixture of learning environments may be necessary for teachers to meet the ISTE standards for digital teaching and learning. Furthermore, there may be a connection between pre-service teachers and their success in e-learning courses due to their intrinsic motivation toward their studies.

Problem Statement

The Covid-19 pandemic has highlighted a growth opportunity for education, focusing on distance and blended learning. Firat et al. (2018) is the first evidence of researchers conducting correlational analysis to determine if motivation varies by sex, degree type, or content model. Murray et al. (2020) followed that research by confirming no significant difference in student experience between online and in-person learning regarding teacher prep programs. Current studies address the unexpected shift from in-person to e-learning across all grades and disciplines, but little research exists focusing on fully online teacher education programs (Ashour et al., 2021; Howard et al., 2021b; Johnston et al., 2021; Mucci-Ferris et al., 2021). With more options available to pre-service teachers than ever before, a gap in the research suggests that there is room to explore whether certain indicators, such as student motivation type, program type, sex, or age, can help students decide which type of college experience is right for them.

Not only is there a need for new research regarding these new and existing online educator preparation provider programs and students' motivations to take and persevere in them, but there is also a need to follow up on more recent research that is centralized around Covid-19. Publications have promoted research regarding the sudden switch to online learning, the troubles with e-learning, best practices for remote education, and opportunities for further study, so follow-ups to the success of these programs and the longevity of online learning opportunities are necessary (Allen et al., 2020; Basal & Eryilmaz, 2020; la Velle et al., 2020, Moorehouse, 2020; Scully et al., 2020). Covid-19 closures mark a shift in e-learning literature.

Both the pre and post-pandemic literature provide historical background on e-learning, its implications, and best practices. Recently, pandemic-published literature has begun to define gaps in the research that can make e-learning a dynamic, functional, and long-lasting trend at all levels of education (Dyment & Downing, 2018; Lee, 2017; Usher et al., 2021). Pandemic learning allowed every educator and learner to develop experience and adapt to a new environment (Barrot et al., 2022; Randi & Corno, 2021). Now, however, is the time to research, develop, and dive further into what makes e-learning work. By studying the connection between a learner's motivation and their perceived success in an e-learning course, we can address the sizable gap in the literature. The problem is that the literature has not fully addressed online initial teacher education from a dynamic, systematic approach (Dyment et al., 2018; Scully et al., 2020) in combination with the students' intrinsic, extrinsic, and amotivation levels (Allen et al., 2020; Firat et al., 2018; Stark, 2019; Yough et al., 2017).

Purpose Statement

The purpose of this quantitative, predictive-correlational study is to investigate a predictive relationship between a student's level of motivation along the academic motivation scale and their perceived success in e-learning environments. This study will compare the predictive variables: IM-to know, IM-toward accomplishment, IM-to experience stimulation, EM-identified, EM-introjected, EM-external regulation, amotivation, sex, age, and program type with the outcome variable: perceived success.

Intrinsic motivation will be assessed using subscales, including the intrinsic motivation to know, to accomplish things, and to experience stimulation (Vallerand et al., 1992). Extrinsic motivation, or the drive to learn due to outside factors, will be assessed according to external, introjected, and identified regulations (Vallerand et al., 1992). Amotivation, or the state of being unmotivated, will also be assessed by the academic motivation scale as well. This study will look at perceived success as a dichotomous successful/unsuccessful variable. Since motivation is a factor that reportedly affects student success in alternative learning environments, literature does exist comparing the two (Lemov & Atkins, 2015; Firat et al., 2018; Fidalgo et al., 2020). However, honing a notably highly intrinsically motivated group, such as pre-service teachers, will be the focus of this study (Brookhart & Freeman, 1992; Chan et al., 2021; Sanderse & Cooke, 2018).

Additionally, gender studies suggest that self-efficacy when learning online differs between males and females, so sex may play a role in the relationship between motivation and success (Wu et al., 2019). Research pertaining to age and experiences in the online classroom suggests that age should also be considered (Lepper et al., 2005; Yoo et al., 2013). In the US, most college students enroll as full-time students, and older students tend to enroll part-time as they juggle more responsibilities. Finally, the type of program students are enrolled in (fully online or blended) will be considered. A program is considered fully online if all classes are attended off campus, and a student is considered to be in a blended program if they attend courses in-person as well as online.

Significance of the Study

This study is unique as it is the first to test the predictive relationship between motivation and perceived success amongst the target population: pre-service teachers. Previous research suggests that educators are intrinsically motivated due to their love of learning, selflessness, and the lifestyle the career offers (Brookhart & Freeman, 1992; Chan et al., 2021; Sanderese & Cooke, 2018; Tang et al., 2020). While research on online educator preparation provider (EPP) programs is an emerging topic of study, as universities develop more diverse online course catalogs, the research pool needs to grow along with the popularity of these courses. The future of post-secondary education is predicted to utilize technology and e-learning beyond proposed expectations (Bustamante, 2020; Duffin, 2020). Colleges, universities, and even secondary schools must have access to accurate research and information. Just as teachers use Gardner's (1983) multiple intelligences to match lessons to their student populations, schools, and counselors can use SDT to match students with programs and environments that best fit their motivations.

While Firat et al. (2018) first derived the relationship between pre-service teacher success and motivation in the e-learning environment through correlational analysis, the study did not focus solely on an EPP program but across multiple disciplines. For instance, Esparragoza (2021) found that intrinsic motivation was not a predictor of e-learning success in an online Spanish class. SDT suggests that high levels of intrinsic motivation lead to achievement in many categories, but the specific population: pre-service teachers, has not been thoroughly tested. Yough et al. (2017) specifically studied motivations and success in teacher preparatory programs but focused on flipped classrooms, not completely online environments. More recently, Zilka (2021) recommends that in response to Covid-19 teacher education courses, a combination of asynchronous lectures and meetings along with asynchronous learning which utilizes 21st-century techniques should be used. Finally, Zilka (2021) suggests that the goals and objectives of online learning should shift the focus away from classroom competencies and more towards the empowerment of the student and the application of these 21st-century skills.

The literature reveals a need for the quantitative study of the three subscales of intrinsic motivation (IM), the three subscales of extrinsic motivation (EM), amotivation, age, sex, and program type for students enrolled in online education courses (Barnes et al., 2020; Buzdar, 2017; Dyment & Downing, 2020; Eom, 2019; Firat et al., 2018; Mahande et al., 2021; Schwam et al., 2020; Starkey, 2019; Wang et al., 2020). The current study will combine Firat et al.'s (2018) findings with the relationship between in-person and online teacher preparatory programs studied by Murray et al. (2020).

The study results should present empirical evidence of the predictive relationship between the variables: IM-to know, IM-toward accomplishment, IM-to experience stimulation, EM-identified, EM-introjected, EM-external regulation, age, program type, and sex, with perceived success. The research should indicate whether or not intrinsic motivation correlates with success for the indicated population. The results can help universities choose which classes to offer online and which might be better suited for in-person atmospheres. Tests like the SAT and ACT predict how high school students will do in college but is just one predictor of overall success. Matching a student's learning needs and motivation portfolios is another predictor and can help a student find the program best for them. However, the question remains, what the correlation is, and whether or not a causal relationship exists? This study will be the first of its kind to test those remaining questions.

Research Question

To explore the perceived relationship between the predictor variables IM (IM-to know, IM-towards accomplishment, IM-to experience stimulation), EM (EM-identified, EM-introjected, EM-external regulation), amotivation, sex, age, and program type with success in an e-learning course for pre-service undergraduate students, the following question guides this study:

RQ1: How accurately can perceived success in an e-learning course be predicted from a linear combination of motivation factors for education students?

Definitions

1. *Age*: Students between the ages of 18 and 24 are “Traditional Age Students,” and those 25 and older are considered “Non-Traditional College Age.” (Monoghan, 2021).
2. *Amotivation:* Having little or no motivation to act or take initiative (Ryan & Deci, 2000).
3. *Autonomy*: Being self-initiating and self-regulating in one's actions (Deci et al., 1991).
4. *Competence:* Understanding how to attain outcomes both externally and internally and being efficacious in performing these actions or achieving goals (Deci et al., 1991; Ryan & Deci, 2000).
5. *E-learning:* a teaching and learning system which is web and technology-based whose primary goal is to provide a personalized, learner-centric, interactive, remote learning environment as an alternative to traditional brick-and-mortar schooling (Rodrigues et al. (2019).
6. *Extrinsic Motivation:* the process of engaging in an activity or practice based on external rewards or needs (Deci & Ryan, 1985).
7. *Intrinsic Motivation:* the inherent need to practice, take action, or partake in an activity for internal satisfaction rather than for eternal rewards or other pressures (Deci & Ryan, 1985).
8. *Motivation:* The study of energy and direction; to be moved to do something (Deci et al., 1991).
9. *Organismic theory:* a theory that stresses the organization, integration, and unity of humans as they grow and develop (Elsasser, 1964).
10. *Pre-service teacher:* an undergraduate or graduate student enrolled in a teacher education program who has not yet spent time teaching in the classroom (Starkey, 2019).

11. *Self-determination theory:* A theory developed by Deci and Ryan (1985) that suggests a tripartite model including autonomy, competence, and relatedness contribute to a person's motivation and success (Ryan & Deci, 2000, 2020).
12. *Self-efficacy:* A measure of a person's belief in their ability, or capacity, to execute behaviors in order to meet specific goals (Bandura, 1997).
13. *Social cognitive theory:* A theory developed by Bandura (1986) suggests that people learn through modeling as they observe and replicate the actions of their teachers and peers.
14. *Success:* Accomplishments or outcomes measured by multiple criteria, including achievement grades, self-efficacy, retention, application, and perception of learning (Stark, 2019).

Summary

In this chapter, the historical background outlined the evolution of distance education to the emergence of the catapulted third wave of e-learning encouraged by the Covid-19 pandemic. The theoretical background introduced theories of motivation and provided background on online teacher education. The social context provided additional information on the pandemic-related settings. Finally, the problem and purpose statements were identified, along with the significance of the study. A potential predictive relationship between the identified variables would have a significant impact on the higher education community and the future of pre-service teacher education.

CHAPTER TWO: LITERATURE REVIEW

Overview

A systematic review of the literature was conducted to explore the relationship between education students' perceived success in e-learning courses and their motivation level. This chapter will present a review of the current literature related to motivation theories, EPP programs, and e-learning courses. The first section will review the relevant theories in motivation. These theories include self-determination theory (SDT) and social cognitive theory (SCT). This predictive correlational study is grounded first in Deci and Ryan's (1985) SDT, which utilizes an organismic theory, and then in Bandura's (1989) behavioral SCT, which favors a model of causation in experiences. In the second section, a synthesis of literature regarding motivation and education and motivation in e-learning will be discussed. Lastly, the literature covering online EPP programs with motivation will be addressed. This section will conclude by identifying the literature gap and presenting the need for the proposed study.

Theoretical Framework

Theories of Motivation

Researchers and practitioners who attempt to differentiate what makes some students succeed or not are at the core of educational research. By studying successful students, researchers and classroom teachers can look for trends, attributes, and characteristics of this population to create interventions for those that do not. Researchers can identify gaps in the demographics such as gender, location, personality type, ability, and more to better understand student actions and achievement in studying the less-successful population. One notable trait that separates high-achieving students from low-achieving ones is a student's motivation level (Wigfield et al., 2019; Wu, 2019). While the conclusion is that motivation is critical for student learning, the literature does not seem to be enhancing, maintaining, or contributing to the field of motivation and how students learn in school at a systemic level (Harackiewicz & Priniski, 2018; Lazowski & Hulleman, 2016). The recent literature calls for more research with an emphasis on motivation theories and practical interventions for classroom use (Harackiewicz & Priniski, 2018; Lazowski & Hulleman, 2016).

Researchers have developed motivational theories throughout history based on needs or behaviors (Deci & Ryan, 1985; Dweck, 2016; Freud, 1957; McClelland, 1965; Skinner, 1957). From the black-box thinkers of the early 20th century to more modern inside-the-box thinkers, the primary framework for motivational science in the 21st century is about understanding personal goals, purposes, and meaning from a complex variety of behaviors (Ryan, 2019b). These theories include achievement emotions, achievement goals, attribution, expectancy-value, goal setting, mindset, interest, needs for achievement, self-affirmation, self-confrontation, self-determination, self-efficacy, social cognition, and social belongingness (Lazowski & Hulleman, 2016). For instance, Watson (1917), the father of motivational science, took a behaviorist approach; Freud (1957) believed that one factor or another drives people to behave the way they do, and McClelland (1965), inversely, saw motivation as a need for achievement. In contrast, Skinner (1957) saw motivation as a product of conditioning and one's environment (Urdan & Schoenfelder, 2006). Dweck (2016) connected motivation to mindset theory. Motivation has been a relevant study of psychology and philosophy for the last two centuries, most notably with SDT and SCT at the forefront of viewing motivation through internal factors.

In recent years, SDT has evolved into a holistic theory that defines students' motivation and tendency to succeed based on a tripartite model (Ryan & Deci, 2000, 2020). The scale defined by SDT correlates to levels of student autonomy, competence, and relatedness. In support of these constructs, SCT predicts how goals and perceived outcomes can strengthen and direct motivation levels through a reciprocal relationship between the student and environmental factors (Bandura, 1986). Although these two theories differ in their premise of how motivation originates, both perspectives stress the importance of student autonomy and appropriate degrees of difficulty of student work when featured in education (Urdan & Schoenfelder, 2006). Furthermore, the SCT construct of self-regulated learning is sustainable through an SDT lens (Schunk, 1989).

Self-determination Theory

Modern research regarding motivation overwhelmingly utilizes SDT to influence, support, and explain their inferences and findings (Howard et al., 2020a; Luo et al., 2021; Manger et al., 2020). Deci and Ryan developed the theory in 1985 when seeking to answer the question: "if a person is involved in an intrinsically interesting activity and begins to receive an extrinsic reward for doing it, what will happen to his or her intrinsic motivation for the theory?" (p. 43). To understand how this question led to the development of a theory, one must first define the three broad types of motivation: intrinsic, extrinsic, and amotivation. Intrinsic motivation is defined as participating in an activity for its inherent satisfaction rather than an external consequence (Deci et al., 1991; Ryan & Deci, 2000). Extrinsic motivation, then, is defined as participating in an activity to receive an eternal reward, benefit, or separable outcome (Deci et al., 1991; Ryan & Deci, 2000). No motivation, or what will further be referred to as "amotivation," is defined in contrast to inherent motivation as the lack of motivation or intent to act (Ryan & Deci, 2000).

According to Ryan and Deci (2000), extrinsic motivation varies on a sub-scale, starting at low payoffs such as external regulation and introjection to the higher-payoff motivations of identification and integration. Intrinsic motivation also falls on a scale, whereas amotivation is a single label. Together, these motivations create the Taxonomy of Motivation (TOM) (Ryan & Deci, 2000). The TOM, as seen in Figure 1, is sized on a scale with non-regulation at the base and moves up towards self-determination. Each scale is organized by regulatory styles. Amotivation has no regulatory markers; extrinsic motivation grows from external to introjected, to identified, and integrated regulation, with integration being the most self-determined extrinsic motivation regulator. Finally, intrinsic regulation has a direct relationship with intrinsic motivation and, therefore, self-determination. Additionally, the perceived locus of causality of learning is shared between EM-integrated regulation and IM-intrinsic regulation.

Figure 1

The Taxonomy of Motivation (Removed to comply with copyright)

[redacted]

Ryan, R. M., & Deci, E., L. 2000. Intrinsic and extrinsic motivations: classic definitions and new directions. Contemporary Education Psychology 25, 54-67.

The relationship between the TOM and the ability to meet a person's three innate and acquired needs: autonomy, competence, and relatedness are at the forefront of SDT (Deci & Ryan, 1985; Deci et al., 1991; Ryan & Deci, 2000). Autonomy refers to being self-initiating and self-regulating in one's actions; the higher the taxonomy, the more autonomous a person (Deci et al., 1991). Similarly, competence grows with the taxonomy. Competence is generally defined as understanding how to attain outcomes both externally and internally and being efficacious in performing these actions or achieving goals (Deci et al., 1991; Ryan & Deci, 2000). Relatedness, on the other hand, involves developing secure and satisfying connections with others (Deci et al., 1991).

Another construct of this theory is the idea of motivation existing as the study of energy and direction. Energy in motivation considers those three psychological needs, whereas direction covers the processes and structures of the response to stimuli in the environment (Deci & Ryan, 1985; Deci et al., 1991). Motivation is a combination of energy and direction, following the internal and external perceived locus of causality (Ryan & Connell, 1989). This combination of energy and direction is a noted construct of SDT. Markedly, SDT is categorized as a motivational theory as it uses motivational constructs while organizing those cognitive, affective, and behavioral variables across multiple domains (Deci & Ryan, 1985).

In contrast to behaviorist theory, an alternative psychological theory known as organismic theory is a theory that stresses the organization, integration, and unity of humans as they grow and develop (Elsasser, 1964). Deci and Ryan (1985) believed that SDT, specifically the study of intrinsic motivation, is necessary for an organismic theory. The theory suggests that because we are born to flourish as living things, there is a natural drive to engage in and master our environments (Ryan et al., 2019). Deci and Ryan (1985) further felt that the central motivator in the educational process must be one's desire to understand and seek answers, and that desire is intrinsic to their being (Ryan & Deci, 1985, 1991, 2000, 2020).

The assumption is that humans have a natural tendency towards partaking in active behaviors towards enhancement. This assumption suggests that people are inherently prone to self-regulation, accomplishment, and understanding (Ryan et al., 2019). Humanity exists within a social world, and individuals move in the direction of autonomy through internalizing and integrating external regulations and behaviors (Deci & Ryan, 1985; Ryan et al., 2019). At the developmental level, the idea extends that students benefit when a teacher supports and establishes student autonomy (Reeve, 2002; Ryan et al., 2019). The educational benefits claim has been supported throughout many research studies between then and now and remains a topic of study for its implications on the learning process (Ryan & Deci, 1985, 1991, 2000, 2020; Reeve, 2002).

Social Cognitive Theory

In 1986, Bandura developed social learning theory based on the idea that learning occurs by watching and imitating others. This social theory of learning developed into what is known as social cognitive theory today. SCT is a perspective that looks at how people are influenced by their environment when it comes to learning, motivation, and self-regulation (Bandura, 1986). Six constructs: reciprocal determinism, behavioral capacity, observational learning, reinforcement, expectations, and self-efficacy build SCT theory (Bandura, 1986). With a focus on learning and doing, SCT is regarded highly in educational settings, specifically when it comes to extended habits and knowledge retention (Reeve, 2002).

SCT displays triadic reciprocal interactions between personal processes, environmental processes, and behavioral processes regarding motivation theory (Schunk & DiBenedetto, 2020).

Bandura’s (1977, 1986) initial work establishes the need for modeling so that students can visualize, process, and repeat what they are meant to learn. This assumption calls for attention to the classroom environment, modeling practices, and social interactions among classmates. Notably, Bandura’s (1977, 1986) construct of self-efficacy has branched into a self-sustained motivation theory of its own (Lazowski & Hulleman, 2016). Self-efficacy refers to the set of beliefs people hold about their ability to complete a particular task. The self-sustained motivational processes include goals and self-evaluations of progress towards those goals, expectations for the outcomes of actions, emphasizing social interactions, and self-efficacy (Schunk & Usher, 2019).

Given the proper environmental and motivational factors, any student can learn (Reeve, 2002; Schunk & DiBenedetto, 2020). The motivational factors highlighted under SCT include goals and self-evaluations, outcome expectations, values, social comparisons, and self-efficacy (Schunk & Usher, 2019). Targeting these factors, however, is the challenge. SCT does predict that appropriate and challenging goals can energize and direct motivational outcomes (Bandura, 1986). This prediction parallels Deci and Ryan's (1985) construct of energy and direction of motivation. An additional crossover of these theories, applied to educational thought, is self-efficacy which remains the most notable link between the two theories (Reeve, 2002; Urdan & Schoenfelder, 2006). Self-efficacy is a measure of a person’s belief in their ability, or capacity, to execute behaviors in order to meet specific goals (Bandura, 1977; Schunk & Usher, 2019).

Self-efficacy appraisals are sourced from four primary sources (Bandura, 1977). These sources include their mastery experiences, modeled experiences, social persuasion, and physiological indexes (Bandura, 1977). Since SCT is a system of triadic reciprocality, self-efficacy is affected by behaviors and the environment around them just as much as it influences them (Bandura, 1977; Schunk & Usher, 2019). The classroom, then, is a breeding ground for these influences. Guidelines for best practice are often reflected in current teaching pedagogies since teaching practices and classroom environments have such a large effect on student self-efficacy and, therefore, their motivation (Schunk & Usher, 2019). The level at which an efficacy appraisal can be conducted outside of a traditional classroom is in question, which threatens students' likelihood of engaging in learning activities to improve their overall knowledge (Schunk & DiBenedetto, 2020; Schunk & Usher, 2019). A thorough review of the literature will address how both SDT and SCT support motivational links to e-learning, focusing on teacher preparation.

Related Literature

Motivation

Simplify defined, to be motivated means "to be moved to do something" (Ryan & Deci, 2000, p. 54). Additionally, motivation can be defined as the reasons for initiating, sustaining, and participating in an activity or action like learning or working (Weiss & Amorose, 2008). Motivation drives the human race to train, accomplish, obtain greatness, think creatively, work hard, foster relationships, and live up to their potential (Deci & Ryan, 1985; Ryan, 2019; Vallerand et al., 2008). A lack of motivation can be detrimental to a person's psyche and the community, as well as the extension, preservation, and potential of all knowledge (Guay et al., 2017; Ryan & Deci, 2000).

Motivation provides the human race with the essential entities needed to direct their power and energy toward performance and passions to lead to a more satisfying and successful life, education, and career (Buzdar et al., 2017). Psychologists have had a hungry interest in what motivates people across all spectrums of motivation for centuries (Ryan & Deci, 2000;

Nakamura et al., 2019). Motivation has implications for almost all successful life endeavors such as personal health, careers, relationships, work goals, sports, hobbies, learning, and more (Deci & Ryan, 1985; Ryan, 2019). However, for all future references in this paper, “motivation” will refer specifically to learning motivation (Buzdar et al., 2017; Deci & Ryan, 1985; Vallerand et al., 2008).

Theories and definitions

Motivation is widely studied and, therefore, widely theorized (Ryan, 2019). Two motivational theories with impregnable associations with academic achievement and student learning are SCT and SDT (Schunk & Usher, 2019; Ryan et al., 2019). As defined above, SCT and SDT have strong correlations and suggest overt overtones toward education. The environment plays a fundamental role in satisfying the three defined fundamental human needs: autonomy, relatedness, and competence (Deci & Ryan, 2985; Vallerand et al., 2008). Environment, then, is the stage in which a person interacts and learns within, according to Bandura's (1986) SCT. Often, these theories can inspire practical interventions for classroom use that promote student learning (Lazowski & Hulleman, 2016). While theoretical research promotes both the veneration of intrinsic motivation and self-efficacy approbation, a universal call for practical interventions reverberates throughout the academic community (Howard et al., 2020b; Lazowski & Hulleman, 2016).

Practice

Research journals are rich with studies regarding motivation theory and, in a few cases, suggest interventions for best practice. Lazowski and Hulleman (2016) conducted a meta-analysis curating resources covering the 16 most referenced motivation theories, supporting that practical, motivational interventions positively affected student learning. When those motivational interventions followed an SDT framework, the effect size increased by 40% in favor of student learning outcomes (Lazowski & Hulleman, 2016). Similarly, Buzdar et al. (2017) conducted a large-scale study (*N*=600) focusing on the TOM's basic constructs concerning collegiate academic performance. The research found that intrinsic and extrinsic motivation has a positive and significant relationship with academic performance (Buzdar et al., 2017). While Buzdar et al. (2017) relied on alternative motivational content and process theories than just SDT or SCT, the results, including additional constructs (challenge, curiosity, and independent mastery), are in support of the Lazowski and Hulleman (2016) interventions conclusions.

SCT suggests that as social creatures, humans have an internal drive to socialize, love, work, share, and learn (Ryan et al., 2019). Classroom practices, learning tasks, student-teacher relationships, peer relationships, and classroom environment each affect a learner's motivation to interact with their environment and succeed (Ryan et al., 2019; Wigfield et al., 2019). Specific to education, intrinsic motivation can be further identified as IM-know, IM-towards accomplishment, and IM-to experience stimulation (Howard et al., 2020a). The sub-theory, which supports the categorization of intrinsic motivation into three levels: to know, towards accomplish, and to experience stimulation, is derived from the three basic psychological needs of autonomy, competence, and relatedness as the primary originators of motivational expression (Deci & Ryan, 2020).

Intrinsic motivation defines carrying out an action based on the joy or satisfaction in doing it (Deci & Ryan, 1985; Heindl, 2020; Vallerand et al., 1992). Child's play is a classic example of intrinsic motivation as spontaneous behavior displays a sense of interest, joy in the process, and a sensorial reaction to one's surroundings (Ryan et al., 2019). Similarly, since learning outcomes are optimized when learners are engaged, creative, and invested in the experience, intrinsic motivation has become glorified in the classroom. While the TOM lists intrinsic motivation as the top tier above extrinsic and amotivation, the distinction between its three subscales: IM-to know, IM-towards accomplishment, and IM-to experience stimulation, must be highlighted.

The intrinsic motivation to know things has a strong tie to education. This subscale relates to constructs such as the motivation to learn, to explore, towards intellectuality, towards meeting learning goals, and toward curiosity (Harter 1981; Vallerand et al., 1992). People who show markers of IM-to know learn for the pleasure of learning. Those with IM-to know motivational markers learn for the thrill of experiencing and absorbing knowledge (Deci & Ryan, 1991; Vallerand et al., 1992).

The intrinsic motivation toward accomplishments is then categorized as mastery motivation (Harter, 1981; Vallerand et al., 1992). Rather than feeling joy for the pleasure of learning, IM-towards accomplishment marks enjoyment at the mastery stage (Deci & Ryan, 1991). IM-towards accomplishment contains constructs in achievement, mastery, extension, fulfillment, and realization.

If IM-to know is the pleasure of learning for learning's sake, and IM-towards accomplishment is the pleasure of learning for the satisfaction of achievement, then IM-to experience stimulation is the pleasure of learning for the process of learning. This generally ties to experiences such as projects, sensory pleasures, excitement, and enjoyment in the learning process (Vallerand et al., 1992). Examples of IM-to experience stimulation include reading a book for cognitive pleasure or euphoria, experiencing brilliant prose, contributing to a lively debate, or for enhancing a group project. The three subscales of IM outline more specific constructs under the umbrella of internal motivation factors, all of which are targeted areas of cognitive, psychological, and educational enhancement studies.

While extrinsic motivation falls in the middle of the TOM, the constructs of each subscale are still worth defining and understanding. Whereas IM pertains to learning for the sake of learning, EM patterns pertain to carrying out a variety of behaviors as a means to an end (Deci & Ryan, 1985, 1991; Vallerand et al., 1992). These behaviors include working hard in school to get recognition, to get good grades, to get a job, or to make money. External regulation is not a bad form of motivation, as many scenarios call for motivation that may not speak to anyone's internal regulations. Instead, when defining the subscales of EM (external regulation, introjection, and identification), the aim is to differentiate between the sources of alternative motivators (Deci & Ryan, 1991).

External regulation is the description of motivation regulated and enforced by an outside force (Deci & Ryan 1991; Vallerand et al., 1992). This construct explains behaviors that are carried out for either reward or fear of punishment. In academic motivation, students who are motivated by their parents, their grades, their reputation, or by a goal such as graduation exemplify IM-external regulation. External regulation can be a powerful motivator at times, but it is not predictive of sustained learning or engagement over time and therefore is not great for retentive learning (Ryan et al., 2019).

With a subtle difference in the source of regulation, IM-introjection defines behaviors that stem from an avoidance of punishment, embarrassment, or in an attempt to improve one's image or self-esteem (Deci & Ryan, 1991; Stover et al., 2012; Vallerand et al., 1992). Introjected regulations spring from ego and one's feelings of self-worth (Ryan et al., 2019). In terms of academic motivation, students who study to do well so that they can impress their peers, who try to prove they are capable, or who do their homework/attend class because they know they will feel guilty if they do not exemplify IM-introjection. This introjection can be validating and lead to self-worth and confidence when approval is validated but can lead to feelings of anxiety or guilt if not achieved (Ryan et al., 2019).

Finally, IM-identification defines decisions made to fit societal norms (Deci & Ryan, 1991; Stover et al., 2012; Vallerand et al., 1992). The most autonomous form of external regulation, IM-identification represents understanding and worth on the part of the individual. The experience of identified regulation is a more internal regulation that identifies the value of an activity itself and can lead to positive outcomes according to societal expectations (Ryan et al., 2019). Students who enroll in a Master of Business Administration because of a societal norm in their industry or students who choose a four-year college over pursuing a trade may be exemplifying IM-identification markers.

If the TOM promotes IM-to know as the highest of motivation, then amotivation is the polar opposite. Amotivation reflects a lack of initiative, lack of action or participation, and disinterest in the task at hand (Deci & Ryan, 1985). The frustration of the basic needs of autonomy, competence, and relatedness contributes to an allover ill-being, dissatisfaction with life experiences, and even failure in school (Ryan et al., 2019). Students who lack direction and purpose in life tend to detach from their teachers, peers, and school in general, which has a direct effect on their learning (Deci & Ryan, 1985; Schwan, 2021). Since one way to measure the internal function of motivation is to measure the external function of student engagement, particularly in a classroom setting, it is possible that the role educators play in engaging students can affect their overall motivation (Hardré & Hennessey, 2013; Schunk et al., 2008; Schwan, 2021). Due to the lack of motivation, direction, and participation synonymous with amotivation, academic success is challenging to achieve for anyone at this end of the spectrum. This correlation poses an obstacle for demographics such as students with ADHD whose disorders can attribute to displays of amotivation in students (Oram et al., 2019).

The idea that motivation can be broken into multiple necessary subcategories is widely accepted (Deci & Ryan, 2020; Howard et al., 2020a; Howard et al., 2020b; Ryan et al.., 2019). However, in a meta-analytical examination of the research, Howard et al. (2020a) found that this tripartite model is redundant and insignificant in the context of student learning and motivation. Identified regulation, introjected regulation, external regulation, and amotivation each relate to different learning indicators and each fall on the TOM (Deci & Ryan, 1985; Howard et al., 2020b). Along this taxonomy, amotivation is universally related to adverse outcomes (Deci & Ryan, 2020; Howard et al., 2020b). Extrinsic or external regulation often correlates to success but with decreased well-being, whereas identifiable, introjected, intrinsic motivations are the only persistent indicators of success (Deci & Ryan, 2020; Howard et al., 2020a; Howard et al., 2020b; Schwan, 2021). While opinions concerning intrinsic motivation as a trilogy or discrete variable differ, both promote the power the construct has over student learning (Deci & Ryan, 2020; Howard et al., 2020a).

Significant studies over decades in SDT research highlight emphasize the vital role that motivation theory has in student learning, teacher effort, and transferability (Levesque-Bristol et al., 2020; Vasconcellos et al., 2020; Wang et al., 2020). Concerning transferability, the ability of students to retain learned knowledge and apply it to the workforce, Wang et al. (2020) confirmed that SDT-related variables explain 64.2% of the between-student variance. Commensurate with Wang et al. (2020), Levesque-Bristol et al. (2020) demonstrated that self-determined motivation, following an SDT framework, is a critical predictor of college students' perceived knowledge transferability. Since transferability is a measure of student knowledge, these research studies compare favorably with Lazowski and Hulleman’s (2016) original findings.

For the same reason that transferability research has aligned with motivation, many research studies propose that SDT interventions be applied to increase classroom performance (Lazowski & Hulleman, 2016; Levesque-Bristol et al., 2020; Wang et al., 2020). SDT training interventions can enhance physical education teacher behaviors and student learning (Vasconcellos et al., 2020). The positive repercussions of theoretical work can convert to practical proposals for positive transformations.

E-learning

Historical references to electronic learning, or e-learning, date back to a 1999 computer-based training systems seminar, but remote learning has a richer history (Lee, 2017). In 1840 Isaac Pitman taught a class in shorthand over correspondence; in 1924, Skinner invented the first "teaching machine," and then in the 1960s, the first proper computer-based training program was introduced (Lee, 2017). In the 1970s, those online systems became more interactive, and as the internet became mainstream, e-learning launched into gear following the Millennium (Zhang & Nunamaker, 2003). Education from the preschool level up through doctoral programs uses e-learning systems (Barbour, 2020). Company training programs, certification programs, development, and personal interest projects alternatively use e-learning systems as well. E-learning has many benefits, including reducing costs, time, and energy, and it engineers worldwide connectivity capabilities (Panigrahi et al., 2018). E-learning has no limit and, in response to the 2020-2021 Covid-19 Pandemic, has grown beyond previous predictions (Duffin, 2020).

Forced online to help stop the spread of Covid-19, higher education students all over the world experienced e-learning starting in the spring of 2020 (Barrot et al.,2021; Hanson, 2021; Moorehouse, 2020). Since then, more research has been conducted assessing the effectiveness and validity of e-learning programs than ever before (Duffin, 2020; Pelikan et al., 2021; Stevanović et al., 2021). Standard variables studied include self-regulated learning, perceived usefulness, student connection, student satisfaction, technology, online LMS, teacher preparedness, best practices, usefulness, and, of course, motivation (Al-Adwan et al., 2021; Stevanović et al., 2021; Turnbull et al., 2021; van der Beek et al., 2020). Providing e-learning training for staff and students, encouraging a sense of online community, and expanding blended learning opportunities in face-to-face courses have each been highlighted as strategies for implementing successful online programs (Turnbull et al. 2021). The future of higher education is unclear. However, technology and e-learning will have an inevitable effect on the longevity, change, or reinvention of college education in the future (Howard, 2020).

Theories and definitions

Technology is considered one of the foremost concerns, innovations, and pathways flanking education today (Landauer, 2020). Teachers and learners utilize technology, teach with technology, and through technology. Educational technology, instructional technology, assessment technology, and assistive technology are all unique subfields within the trend. e-Learning, then, should be defined to establish its unique position within the education field today. e-Learning is a web-based system based on digital technologies and other forms of educational technologies whose goal is to provide students with a learning environment that are personalized, learning-centered, open, and enjoyable (Howard, 2020; Park & Shea, 2020; Rodrigues et al., 2019). e-Learning promotes a better, more engaging learning environment and leads to more advanced understanding and physical outcomes (Park & Shea, 2020; Rodrigues et al., 2019). E-learning does not explicitly occur remotely, formally, or singularly online by definition (Park & Shea, 2020). However, for this paper moving forward, those assumptions will be developed.

Naming is often just as important as the person, concept, or idea the name identifies; educational constructs are no exception. Howell (2020) argues that the title educators use as descriptors of their job (i.e., educator, instructor, or teacher) is just as important as naming a newborn infant. Conducting research involving e-learning requires multiple search domains. Electronic learning is the term used in Thesaurus ERIC, while e-learning is the synonym most commonly used, but online or mobile learning is also prevalent (Valverde-Berrocoso et al., 2020). Howard (2020) analyzed 31recent articles covering 36 keywords to determine teachers' names for multiple teaching settings, settling on online instructors, distance educators, and sojourn teachers online by choice, forced remote, and situationally remote teachers, respectively (Howard, 2020). While Valverde-Berrocoso et al. (2020) refer to the course atmosphere and Howard (2020) refers to the instructor, both develop the defense that students and teachers must understand their learning experience parameters. The unique factors that separate blended learning from hybrid, an online instructor versus a sojourn teacher, and a distance education class versus a technology-based learning course would affect student/teacher mindset, expectation, and, potentially, achievement (Park & Shea, 2020).

E-learning and Motivation

As crucial as naming and identifying e-learning is, the impact that the endeavor is making on the field is potentially more paramount. The format in which teaching and learning occur can affect the velocity, level, enjoyment, and retention of knowledge, which should be highly considered when paralleled with motivation (Lemov & Atkins, 2015). The intensity, direction, speed, and persistence of human behavior are directly affected by human motivation (Firat, 2018). Unfortunately, literature reviews and research studies suggest that motivation is considered one of the main factors hindering online education (Eom 2019; Luo et al., 2021; Mahande & Akram, 2021; Hongsuchon et al., 2022). Whether this is a result of preconceived notions, a common misconception, an inadequate program, or teacher quality, the suggestion can deter students from taking online classes or affect their mindset (Eom, 2019; Fidalgo et al., 2020). Research shows, however, that through motivational teaching interventions and student-study match algorithms, e-learning can be a practical education setting (Eom, 2019; Mahande & Akram, 2021; van der Beek et al., 2020). Moreover, Firat et al. (2018) deduced no significant difference in students' motivation based on instruction type, which varied from in-person to blended to distance education. This deduction was mirrored in student self-regulatory success as well (van der Beek et al., 2020).

A multinational study regarding students' perception of e-learning reveals that one of the principal reasons students may not enroll in an online class is their adversity when trying to stay motivated (Fidalgo et al., 2020). A higher dropout rate for e-learners exists. For this reason, studies concerning motivation and e-learning are compulsory. Intrinsic motivation is a prerequisite for sustainability in an e-learning course (Firat et al., 2018; Hongsuchon et al., 2022). The proposed reason that intrinsic motivation is a necessary disposition is that, for e-learning environments, in particular, learners' study on their own and need that autonomy, self-reliance, and internal motivation (Firat et al., 2018; Hongsuchon et al., 2022; Ng 2019). Moreover, motivation is not just a prerequisite for e-learning but also an enabler for online learning (Ng, 2019).

Similarly, Moore’s (1993) theory of transactional distance (TTD) supports the role of learner autonomy in e-learning. Deemed the very first theory related to distance education, the TTD explored the relationship between classroom structure, teacher dialogue, and student autonomy (Moore, 2018). The theory explains that all e-learning programs fall on a hierarchy between the top-tier learner-determined programs and the low-tier, non-autonomous teacher-determined category (Moore, 2018). The theory explicitly promotes the role that student autonomy plays in successful learning, a suggestion mimicked in both SDT and SCT. During the Covid-19 shutdowns, it became more evident that the distance between individuals in cyberspace is not physical but psychological: the very paradigm shift that the TTD describes (Paul et al., 2022). The new scale for measuring transactional distance even accounts for differences in gender and mode of delivery for a more accurate measure and indicator of successful e-learning programs (Paul et al., 2022).

Synchronously, researchers agree that SDT correlates to successful e-learning programs (Fidalgo et al., 2020; Firat et al., 2018; Mahande & Akram, 2021). SDT's influence on instruction relates to multiple capacities (i.e., increasing interest, educational assessment, and technological confidence) of intrinsic motivation and student success (Mahande & Akram, 2021). Hui-Ching et al. (2019) established a path from the learning environment to needs satisfaction, then to motivation and learning outcomes within the SDT framework. Earlier studies, such as that by Chen and Jang (2010), were unable to show that SDT was able to predict learning outcomes in online climates, but since then, the research has been able to show the predictive relationship between SDT constructs and e-learning success (Fidalgo et al., 2020; Hue-Ching et al., 2019; Mahande & Akram, 2021).

A derivative of SCT, the attention-relevance-confidence-satisfaction integration model, can also promote achievement autonomy motivations while enrolled in online classes (Mahande & Akram, 2021). A secondary concern facing online student learners, distinguished by Eom (2019), was the lack of student interaction. Furthermore, Hongsuchon et al. (2022) link the lack of student interaction to both student motivation and the employment of strategic online learning strategies. SCTs reciprocal learner-atmosphere relationship supports this discovery. Motivated distributed environments, whose aim is to situate e-learners at the center of flexible systems with multiple pathways for learning content, accessing resources, and utilizing instructor support, have continued to develop over the past 40 years (Ng, 2019). These distributed learning systems manage to enhance accessibility and differentiation while empowering learners. Like Dyment and Downing (2018), Ng (2019) found that modern research has shifted from whether or not learners can be motivated to learn online, but instead how to best support these learners and their needs online to enhance their motivation. Importantly, research suggests that prior experience with technology, the Learning Management System (LMS) and computer experience can affect the way students perceive their e-learning outcomes (Eom, 2019). Furthermore, a student's learning style, motivation, engagement, and self-efficacy scores have a magnified impact on their e-learning experience (Eom, 2019).

Hongsuchon et al. (2022) found that highly motivated students could easily, efficiently, and comprehensively adopt effective online learning strategies. The students who identified as having higher motivation levels also had higher learning effectiveness online than those with lower motivation scores (Hongsuchon et al., 2022). This research suggests that stimulating students’ interests in learning and nourishing their motivation to learn can have a positive effect on their ability to thrive in an e-learning context. Between fostering the motivation to learn, enhancing the online learning environment, and employing strategic learning strategies, e-learning has grown into a realistic platform for successful and enjoyable learning. The combined research confirms that motivation is a significant factor in student learning and that motivation interventions, demographic and personality characteristics, and perception characteristics should be further investigated (Eom, 2019; Fidalgo et al., 2020; Firat et al., 2018; Hongsuchon et al., 2022; Mahande & Akram, 2021).

Educator Preparation Provider Programs

Schools are only as stable as their teachers, and teachers are only as strong as their education programs train them. Teacher education programs differ in size, shape, and requirements throughout the country, with each state framing the guidelines and certifications required of their pre-service teachers (Davis & Peck, 2020). Time spent in the college classroom has unique influences on a future teacher's understanding, efficacy, and beliefs (Starkey, 2019). Following SCT insights, beliefs are personal cognitive conceptions formed by behavior, environments, and external stimulants (Civitillo et al., 2018). During this time, teachers can develop and perpetuate certain "learning myths" that can then transfer to non-educating community members (Rogers & Cheung, 2020). Pre-service teachers should have access to vital teacher education programs that can adequately prepare them for current and future schooling contexts. Research on EPP programs should expect to change and adapt as digital platforms, instructional technology, and innovative infrastructure are introduced and established within modern schooling systems (Davis & Peck, 2020; Starkey, 2020).

EPP Programs and E-learning

As the world transforms and adapts to challenges, advances, and shifts, including online and blended learning, schools of education must recognize and stay ahead of these changes to best prepare novice teachers. In March of 2020, most US and worldwide universities shut down or shifted to online learning platforms forcing EPP programs to go remote (Gillis & Krull, 2020; Murray et al., 2020). The mandatory movement to e-learning, consistent with SCT and SDT theory, affected the autonomous feeling of control students have when choosing their course structures (Murray et al., 2020). During this time, all-online colleges and universities, such as Western Governors University, prevailed as their students were all able to function throughout the pandemic crisis (Barnes et al., 2020). Initial teacher education programs that were not already operating online had an adjustment period, just as K-12 classrooms worldwide did. Initially a growing field pre-pandemic, online initial teacher education is more prominent than before, yet there remains limited mention of "best practices" for online delivery in modern research reports (Dyment & Downing, 2018)

Teaching style is one crucial factor for e-learning success, but course structure and content are another. Starkey (2020) reviewed research exploring EPP programs and defines three digital competencies unilaterally found within the programs: generic digital competence, digital teaching competence, and professional digital competence. Within the newest competency, professional digital competence, teachers should master many competencies. These competencies include teaching using technology, teaching students as they use technology, managing technology in the digital and virtual environment, using Learning Management Systems, using data analysis tools, participating in learning networks, and using communication tools (Starkey, 2020).

SCT suggests that pre-service teachers must learn to teach in digital environments in order for them to learn in an immersive digital environment (Barak, 2016). In 2019, 46% of university faculty members reported teaching at least one online course (Bustamante, 2020). This pre-pandemic statistic shows the trend towards blended or online learning becoming more mainstream than in the past. Five years ago, research regarding initial teacher education was always comparative research juxtaposing online programs to brick-and-mortar schooling (Dyment & Downing, 2018). Recently, the popularization and acceptance of e-learning have led to a transition to maximization research instead (Dyment & Downing, 2018). This shift demonstrates the advancement and social understanding of online teacher education programs.

Teachers and students view e-learning from contrasting lenses, yet pre-service teachers experience both viewpoints simultaneously (Daniels et al., 2019). Both the teacher and student perceived technology self-efficacy, ease of use, and usefulness of content as principal factors affecting technology use in online teacher preparatory courses (Al-Maroof et al., 2021). Yakovleva (2022) found that pre-service teachers value digital learning content but are not sufficiently ready to create that content. A call for professional training and experience within digital learning environments is supported (Al-Maroof et al, 2021; Dyment & Downing, 2018; Yakoleva, 2022). As online degrees and select digital courses grow in popularity, teacher and student competency should increase.

EPP Programs and Motivation

Having a passion for a subject and wanting to instill that passion in their students is among the most frequently mentioned reasons for a career in education (Sanderse & Cooke, 2018; Tang et al., 2020). This finding exemplifies the inherent, intrinsic motivation of many pre-service teachers. Additionally, millennial pre-service teachers report that intrinsic motivation is the defining factor influencing initial teacher education and professional competence today (McLean et al., 2019; Tang et al., 2020). Examining the relationship between students' motivation levels with beginning teacher outcomes, McLean et al. (2019) concluded that millennial abilities and intrinsic values translated to career optimism and less burnout than past generations. Tang et al. (2020) confirmed this result and added that meaningfulness, financial security, work-life balance, and personal-professional goals were also factors in high pre-service teacher motivation levels.

Interest in teaching and the subject taught are important motivators for millennial pre-service teachers (McClean et al., 2019; Sanderse & Cooke, 2018; Tang et al., 2020). However, self-development and an ideal lifestyle characterized this interest as well (McClean et al., 2019; Tang et al., 2020). These personal well-being motivators meet the core psychological characteristics necessary for learning according to SDT: autonomy, competence, and relatedness. For instance, second-career teachers report lower levels of job stress and higher levels of job satisfaction and self-efficacy than their prior careers, thus promoting career teachers' mental health (Troesch & Bauer, 2017). Furthermore, "ideal lifestyle" could be attributed to more flexible initial teacher education programs made available through blended or distance education platforms as well as increased access to underserved communities who otherwise may not be able to attend classes (Andrade & Alden-Rivers, 2019). Teacher education programs generally include a student-teaching model where students learn in a subversive environment stabilized by SCT theory to grow more confident and autonomous and relate to their future careers.

The world needs more than 69 million teachers, and the success of initial teacher education programs has a significant effect on these shortages (Goldhaber et al., 2020; UNESCO, 2019). Education programs around the world are failing to adequately prepare new educators for the job ahead, and some regions are employing unqualified teachers with no training at all (*Education*, 2021). Confidence, autonomy, and content knowledge are the basic needs of pre-service teachers everywhere. Luckily, pre-service teachers are intrinsically motivated to learn when their EPP programs provide clear instruction, support, and feedback and when they teach student autonomy and relatedness (Chan et al., 2021a; Lazarides et al., 2019). Not only is the perception of support and feedback positively associated with student intrinsic motivation, but the strongest predictor of high intrinsic motivation is also a significant predictor of behavioral and cognitive engagement during the learning process (Chan et al., 2021b). The bidirectional relationship between motivation and success in an EPP program may be the key to recruiting, training, and placing pre-service teachers worldwide.

Work-life balance and a calling to teach are some examples of aims to enter the field of education, but passion for a specific subject area or content is another. Alternative route educators who switch from working in a field they are passionate about instilling that passion in their students are prime examples of content-driven educator motivators. Department variables can alter the motivation levels of future teachers. Titrek et al. (2018) found that prospective teachers in the sciences and psychological/guidance departments are higher motivated than those in the English department. A related study by Sahin and Caker (2011) again found that perspective teachers in science and physical education programs were higher motivated than those preparing to teach music.

The ability to work with adolescents is the final motivator defined by students in EPP programs. A desire to shape the future of children and adolescents was highlighted as a strong motivator for pre-service teachers looking to enter the industry (Fokkens-Bruinsma & Canrinus, 2014; Nesje et al., 2017; Tang et al., 2020). Instilling a love for learning and making an impact on the future contribute to one's intrinsic motivation in the profession. The motivation and dedication to their students and careers were discerned as a top marker for teacher retention (Casely-Hayford et al., 2022; Goldhaber et al., 2020). While social support and the health state of teachers are also critical to retaining effective teachers, fostering teacher-student relationships, promoting a positive work-life balance, understanding the motivations of different subject areas, and an increase of holistic, engaging, and self-confidence creating initial teacher education programs will help slow the teacher shortage the world is currently facing (Casely-Hayford et al., 2022; Chan et al., 2021a; Lazarides et al., 2019; Tang et al., 2020)

EPP Programs, E-learning, and Motivation

The high levels of intrinsic motivation inherent to initial teacher education students, as derived by McClean et al. (2020), explain the variance Firat et al. (2018) established when addressing distance education students' intrinsic motivation levels. The correlational analysis shows no significant differences in motivation by sex, degree type, or instruction type, implying that motivation can be consistent between distance education and blended programs between undergraduate and graduate levels and between genders (Firat et al., 2018). Furthermore, Murray et al. (2020) declare that emerging literature confirms that there is no significant difference between online and in-person learning regarding teacher education. While the literature supports online initial teacher education, a considerable research gap regarding online initial teacher education and motivation still exists.

A particular demographic which does have a recognized propensity towards internal regulation is nontraditional college-age students. Shillingford & Karlin (2013) found that nontraditional age (25+) pre-service teachers endorsed an internal desire to demonstrate competence, feelings of self-determination, and recognized the pleasure and satisfaction of experiencing the college environment. The drive to learn and experience school was more substantial for this age group than the extrinsic motivation of career advancement (Shillingford & Karlin, 2013). Fifteen percent of all full-time undergraduate students in the United States are of non-traditional college age (NCES, 2022). Additionally, fifteen percent of all teachers enter the profession in their late 20’s, sixteen percent in their thirties, and nine percent enter after age forty (NCES, 2012). Knowing that nontraditional-age students are more disposed to enroll in e-learning courses than traditional-age students, these facts combine to suggest how many non-traditional-age students may be enrolled in online EPP programs (Carreira & Lopes, 2021).

Furthermore, the role of gender in motivation studies has a rich history as well (Schunk & Usher, 2019). In an instructional setting, students' self-efficacy may be affected by sex and content factors (Chan, 2022; Meece & Painter, 2008; Tzu-Ling, 2019). In high school and beyond, the self-efficacy of males can predict success in STEM courses due to gender disparities, interests, and cultural gender norms (Chan, 2022; Tzu-Ling, 2019). These gender disparities are essential because they can affect career trajectories and quality of life (Tellhed, Backström, & Björklund, 2017). Further, Al-Jaberi (2018) concluded that males and females differ in their attitudes toward computer programs and e-learning, which gave them an advantage in post-secondary education. However, Hatlevik and Bjarnø (2021) found that student teachers’ motivation, including resilience to digital distractions, was positively correlated with their approach to studying and learning for female students only. Similarly, Kirk (2020) found that female pre-service teachers with intrinsic or extrinsic motivation could buffer stressful situations and persevere in their Bachelor of Education courses; only males with intrinsic motivations could. How the sex of pre-service teachers in e-learning courses correlates with their motivation overall is still yet to be determined.

Demographics aside, the post-pandemic perspective is that a concentration on the most forgotten SDT construct of relatedness should level out with the trendy “autonomy and competence” for conceptualizing relatedness in education (Murray et al., 2020, p. 498).

Relatedness addressed an ethical urgency to connect with learners, therefore, creating a more critically oriented teacher prep program that encourages human connections and emphasizes a more authentic and relatable way (Murry et al., 2020). While a direct relationship between perceived social relatedness and procrastination is ambiguous, evidence shows that learning behavior, as impacted by relatedness measures, can be mediated by strong intrinsic motivation patterns (Pelikan et al., 2021). If teachers tend to score high on the intrinsic motivation scale, then their preconceived notion toward relatedness can increase their ability to learn remotely. Another variable in operation is the simultaneous work towards professional and academic goals. If pre-service teachers are both students and teachers at the same time, their motivations might be a mixture of seeking professional outcomes along with academic ones (Daniels et al., 2019). This idea suggests that the motivations of pre-service teachers might shift throughout a university's program

The 2020-2021 Covid-19 pandemic not only catapulted e-learning beyond its predicted trajectory in feasibility and acceptance, but it opened the doors for further research on motivation, student achievement, and the purpose of education altogether. Publications detailing the transition from in-person teacher preparation programs to remote situations during the Covid-19 pandemic are funneling in, with studies reflecting on this transition, including student impressions, best practices, mishaps, and opportunities (Allen et al., 2020; la Velle et al., 2020; Moorehouse, 2020; Scully et al., 2020). The success of these online programs and the perceived success of each future teacher is worth studying. Further follow-up information on the longevity of these e-learning opportunities and student learners' motivation at this time have not yet been published. The widespread use of e-learning platforms for initial teacher education may lead to more research in the field and help bridge the gap between online initial teacher education and intrinsic motivation.

Summary

Research covering motivation and online learning is an emerging and necessary topic in today's ever-growing digital climate (Barnes et al., 2020; Firat et al., 2018; Mahande & Akram, 2021). Motivation is responsible for human achievement and has been credited to maximization research (Guay et al., 2017; Ryan, 2019; Ryan & Deci, 2020). The literature suggests several applications of motivation theory in response to the growing field of distance and online learning. E-learning itself comes in many shapes and forms and is an ever-increasing topic of discussion in K-12 and higher educational settings. In addition, several conclusions can be drawn from the review of the literature related to a student's TOM level and their perceived success in both traditional and electronic learning experiences.

Leveling measures of motivation into a spectrum of motivation scales such as the TOM has been supported by researchers for the last two decades (Deci & Ryan, 2000). Specific to the field of education, ranking a student's level of relatedness towards learning can help predict their autonomy and competence in school. If organismic theory suggests that humans are pre-destined to interact with their surroundings and form relationships in order to master their environment, those with high levels of intrinsic motivation are more likely to succeed in school (Deci & Ryan, 1985). This review of the literature has provided examples of each of the seven scales of the TOM and how each might present in an online setting.

One aspect of motivation theory in both SDT and SCT is the social-relatedness and learning environment present in schools. Debatably, online classrooms concern themselves with student motivation opportunities. Due to digital advancements, the 2020 pandemic, affordability, and accessibility, schools are pushing flexible course offerings more than ever. Online course types, such as in-person, blended, virtual synchronous, or distance asynchronous learning models, represent independent sectors of e-learning practices (Fidalgo et al., 2020; Mahande & Akram, 2021). With these digital advancements, pre-service teachers are pushed to experience e-learning content from the perspective of a student and from that of an instructor. Self-efficacy and experiential confidence can affect the way pre-service teachers eventually succeed in school and within the walls of their classrooms.

How motivation explicitly affects pre-service teachers' perceived success in e-learning courses is still up for debate. SDT and SCT constructs work to maximize a person's output and suggest that motivation can be the key to unlocking online platforms' full potential (Ryan & Deci, 2020; Panigrahi et al., 2018). More specifically, SDT-based studies indicate that e-learning students with higher intrinsic motivation levels will have more success in e-learning education programs than those who do not (Howard et al., 2019). The literature is rich with correlations between predictor variables such as sex or age and their effect on student motivation scores. Furthermore, sex and whether or not a student is categorized as “traditional college age” or not may help predict perceived success both in their field of education and in online courses.

People of all ages, genders, ethnicities, backgrounds, and cultures pursue a career in education for the love of content, the love of learning, the reward of helping others, and the relationships built with students. Flexible pathways in higher education attract a similarly diverse demographic pool for some of the same reasons. Flexibility, affordability, convenience, and learning style are all reasons why someone might take an online course (McClean et al., 2019; Sanderse & Cooke, 2018; Tang et al., 2020). Although investigations have demonstrated that pre-service teachers have high intrinsic motivation levels, a specific and notable gap in the research is the correlation between online education students' motivation levels with their overall achievement and satisfaction in that course (McClean et al., 2020).

In this chapter, the theoretical frameworks of motivation were delineated. Motivation in correspondence with e-learning and EPP programs was also discussed. Additionally, themes of current literature related to the research topics were presented, and gaps were presented. This study aims to narrow the gap and understand whether or not specific concentrations, like initial teacher education students, are predetermined to succeed in the e-learning setting due to their motivational proclivities. Next, in Chapter Three, the methodology and data used to investigate the research question will be described.

CHAPTER THREE: METHODS

Overview

The purpose of this quantitative, predictive-correlational study is to investigate a predictive relationship between students' motivation and their perceived success in e-learning environments. As measured by one's inherent, self-driven intrinsic factors versus externally manipulated factors, motivation measures one's desire or willingness to do something. Success is the outcome of an undertaking and can be measured through several tools and standards. Chapter Three discusses the study's research design, research questions, hypotheses, participants and setting, instrumentation, and data analysis.

Design

The study utilizes a quantitative, predictive-correlational design to determine if an association exists between motivation levels, amotivation, sex, age, program type, and perceived success (Gall et al., 2007; Salkind, 2010). Additionally, the predictive-correlational research design seeks to find the association between the predictor variables (motivation subscales, sex, age, and program type) and the outcome variable (perceived success). Furthermore, the predictive-correlational design allows the researcher to study educational phenomena that cannot be studied without experimental methods (Gall et al., 2007; Patten & Newhart, 2017; Warner, 2013). The predictor variables are extrinsic and intrinsic motivation levels, amotivation, sex, age, and program type, whereas the outcome variable is perceived success (Deci & Ryan, 1985; Eynon & Malmberg, 2020; Veletsianos et al., 2021).

Predictive-correlational research is a research design used to investigate the magnitude and nature of a relationship between predictor and outcome variables (Sheskin, 2010). The predictive-correlational design is a measure of correlation and is descriptive in nature. It is prudent to note that results cannot draw conclusions about a cause-and-effect relationship between the defined variables (Sheskin, 2010). Typically, data where a correlation coefficient is computed are also evaluated with regression analysis to derive an equation to estimate or predict a subject's score on one variable from their score on another (Gall et al., 2010; Sheskin, 2010).

Correlational research designs are used for two major purposes: to explore cause-and-effect relationships between variables or to predict scores on one variable from scores on other variables (Gall et al., 2007). The essential feature of a predictive-correlational design is that it is a non-experimental study; researchers observe and describe current conditions or scores and look to predict possible associations with outcome scores (Patten & Newhart, 2017; Warner, 2013). In prediction research, the predictor variables are usually collected and measured prior to the measurement of the outcome variable (Gall et al, 2007; Patten & Newhart, 2017).

A few key steps must be followed when planning a predictive-correlational study:

1. A researcher must speculate about a potential association or correlation that interests them. These speculations can be based on observation, prior research, or theory.
2. The researcher should declare a statement about the research problem in the form of a hypothesis. In stating the research hypothesis, an alternative hypothesis should also be stated. The criterion should be properly defined at this stage.
3. The researcher should draw participants from the specific population pertinent to the study.
4. Next comes the data collection stage. Any measuring instrument can be used in the data collection stage, including standardized tests, questionnaires, interviews, or observations for both the predictor and outcome variables. However, the predictor variables is usually measured prior to the collection of data for the outcome variables. It is important to note

that the prediction of short time behavior is almost always more accurate than the prediction of behavior that will occur in the more distant future, so it is recommended that you keep the time-span of data collection as succinct as possible.

5. Next comes the data analysis stage. Correlating scores on each predictor measure with the criterion scores is the primary method of data analysis for predictive-correlational studies. Then, other statistical techniques can be applied to improve predictions. Data analysis techniques include using Person's correlation, bivariate regression, multiple regression, and logistic regression.
6. Finally, researchers should interpret and present the correlational findings (Gall et al., 2007).

Throughout this research design process, specific requirements regarding data collection, analysis, and interpretation are required. While the data collection process is open to a plethora of instruments, the researcher should ensure that they are clearly defining and measuring each of the designed variables. Once appropriate data analysis is complete, cautious and precise interpretation must occur. In the interpretation phase, the researcher can either infer a positive or negative relationship between variables or determine that a relationship does not exist.

One advantage of correlational designs is that multiple variables can be addressed. A predictive-correlational design is an economical, approachable research design model that can detect associations between variables without the need for experimental interventions. One disadvantage is that correlational research is often misconstrued or mistaken. To ensure that relationships are valid and significant, researchers should always consider confounding variables and alternative hypotheses. It is also crucial that the researcher clearly defines each variable within the context of each study and chooses the appropriate test for the identified variables (Gall et al., 2007; Patten & Newhart, 2017).

Predictive-correlational research is often a result of an observed phenomenon, an academic hypothesis, or is related to the researcher's passion. This research design utilizes quantifiable data such as ordinal or interval data making the results and relationships easy to interpret for stakeholders and other readers. One advantage of this correlational design is that many variables can simultaneously be tested for associations and predictive relationships. However, confounding variables, alternative hypotheses, and misinterpretations can lead to the spread of misinformation. For these reasons, the predictive-correlational design addressing the described research question is a quantitative study investigating the predictive relationship between the identified predictor variables and the outcome variable: perceived success.

The outcome, or criterion variable, perceived success, will be measured as either "perceived successful" or "perceived unsuccessful" as determined by student self-report. Students were asked to score their relationship with two statements according to a 7-point Likert Scale. The Likert ranges from 1, “does not correspond at all,” to 7, “corresponds exactly.” The first success statement says “I earned good grades in courses I have taken online.” The second statement reads, “Online courses are effective and help me to improve my learning and understanding.” By rescaling Likert data to dichotomize the response, a total score range of 11-14, re-scaled to a “1” success level will indicate “perceived successful,” whereas a total score range of 2-10, re-scaled to a “0” success level will indicate “perceived unsuccessful.” See Figure 2. Re-scaling, or collapsing, Likert data provides researchers the flexibility and freedom to use more accurate forms of self-report, such as 5 or 7-point Likert scales, without sacrificing the ability to use clean dichotomous or trichotomous variables in their research. Other academic studies have used this re-scaling Likert data methodology to maintain dichotomous research capabilities (Ayres et al., 2019; Grimbeek et al., 2005; Jeong & Lee, 2016; Khalafallah et al., 2020; Masselink et al., 2020).

Figure 2
Re-scaling to Dichotomize a 7-Point Likert

Original 7-Point	1	2	3	4	5	6	7
Total Score Range	2-10					11-14	
Dichotomized	0					1	

This research utilizes the criterion variable, "perceived success," not the variable "success." While both variables suggest attainment of achievement or a sense of victory, perceived success focuses on the more subjective view of how a participant feels they have performed. In contrast, success is often measured objectively (Almarabeh, 2014). Then, success in an online course can be measured according to a grade in a course, student GPA, attendance, final exam score, teacher impressions, or other criteria. While these hold value in their mostly objective nature, the variable fails to measure the value the course held for a student, the effort they put in, the transference to real-life application, or a student's confidence in their mastery. For this research, a more stringent definition of "perceived successful" was used to divide students into two groups based on the assumption that students would be hesitant to predict their own lack of success in a course they have not yet taken. As shown in the dichotomized re-scaling, students who score a cumulative score of 11-14 are categorized as "perceived successful" and those scoring between a ten and two will be "perceived unsuccessful."

As subjective as a student's self-assessment of success may be, the value added in terms of those additional success markers is more valuable in the field of teacher preparation under the lens of SDT. SDT and SCT value goals and perceived outcomes (Bandura, 1986; Ryan & Deci, 2000). Since SDT is a key predictor of perceived knowledge transfer and perceived locus of causality, student perceptions of e-learning and their perceived success present a stronger criterion variable than an “objective” success variable (Almarabeh, 2014; Levesque-Bristol, 2020; Ryan & Connell, 1989).

The ordinal predictor variables are the motivation levels. Levels of motivation will be categorized with a score for IM-to know, IM-toward accomplishment, IM-to experience stimulation, EM-identified, EM-introjected, EM-external regulation, and amotivation. Intrinsic motivation is the internal motivation to succeed and is broken into three levels: to know, to accomplish, and to experience stimulation (Ryan & Deci, 1991; Vallerand et al., 1992). Extrinsic motivation is the drive to learn or accomplish as affected by outside factors and is ranked as external, introjected, or identified regulations (Vallerand et al., 1992). Amotivation is the lack of motivation or the state of being unmotivated (Deci & Ryan, 1991; Vallerand et al, 1992). Next, the categorical variables age and sex were categorized. Sex refers to the participants' anatomy and may be listed as male, female, or other. Age refers to whether or not a person is a traditional-aged college student. Participants were labeled as Traditional College Age (18-24) or a Non-Traditional College Age (25+). Students also indicated whether they were enrolled in an online EPP program or if they were an on-campus student taking an online course.

This quantitative, correlational study investigates a predictive relationship between a student's level of intrinsic, extrinsic, and amotivation and their perceived success in e-learning environments. This study will compare the predictor variables: intrinsic motivation, extrinsic motivation, amotivation, sex, age, and program type with the dependent variable: perceived success. With so many independent variables, the study can determine if a predictive relationship exists between any of the predictor variables with a single dichotomous dependent variable:

perceived success. A correlational model was necessary since the research seeks to predict one outcome from the measure of initial variables.

Research Question

RQ1: How accurately can perceived success in an e-learning course be predicted from a linear combination of motivation factors for education students?

Hypothesis(es)

The null hypothesis for this study is:

H_0: There will be no significant predictive relationship between the criterion variable "perceived success" and the linear combination of predictor variables (IM-to know, IM-toward accomplishment, IM-to experience stimulation, EM-identified, EM-introjected, EM-external regulation, sex, age, and program type) for online pre-service teachers.

Participants and Setting

Population

The population for this research study includes students at the prominent university enrolled in an online or in-person EPP program. The population includes post-secondary students of all ages, backgrounds, sexes, and ethnicities. The students in the study are most likely pre-service teachers and would be taking an online initial teacher education course for any reason. The target population includes students taking a class online, but their program could be blended or fully virtual. The targeted population specific to this study are all students taking online education courses at a particular private, non-profit university in the southeast United States that has a prominent online education program.

Participants

The participants of this study were drawn from a convenience sample of undergraduates from the targeted population during the summer semester of 2023. For this study, the number of participants sampled was 68, which exceeded the required minimum sample size for correlational analysis when assuming a medium effect size with a statistical power of .7 and alpha level, $\alpha = .05$ (Gall et al., 2007, p. 145). When assuming a medium effect size with a statistical power of .7 at the .05 alpha level, 66 students are required. The researcher selected the participants for convenience because the students were volunteers and because of the appropriate representation of the generalized population (Gall et al., 2007).

In the end, 68 volunteers were solicited by the researcher from a pool of undergraduate male and female students. The study included a minimum of 15 male students, 15 female students, and 5 students who identified as “other.” Specifically, the participants included 58 females, 10 males, and no students of the unknown or alternative sex. For this, “other” was excluded from the analysis. All students were undergraduates enrolled in an online education course, but 20 were categorized as "traditional college-age," and 48 were categorized as “non-traditional college-age.” Of those of traditional college age, 6 were male, 14 were female, and 00 were other. Of those of non-traditional college age, 4 were male, 44 were female, and 00 were other.

Setting

The participants were all enrolled in an undergraduate online teacher education course from the target population. The school has over 100,000 students, with 30,000 military students and 700 international students. There are over 700 programs offered, including over 450 online programs. Of the online programs, over 100 are undergraduate, 300 are graduate, and 75 are doctoral programs. 40% of online students are male, and 60% are female. 60.7% of undergraduates are Caucasian/white, 8% are black or African American, 5.7% are Hispanic, and the remaining are minorities or unknown. Additionally, 18.5% of students fall into the "average age" of a college student between 18-21, whereas the national average is 60%. Instead, 56.3% of all students are 25 and over (collegefactual.com). The course the participants were pulled from was EDUC 201 online. The data was collected online through the participants' course LMS and the University's preferred survey instrument: Qualtrics. Data collection occurred at each participant's convenience within the first three weeks of the semester. The setting was designed to match other assignments within the course for familiarity and ease of access.

Instrumentation

The predictor variables IM-to know, IM-toward accomplishment, IM-to experience stimulation, EM-identified, EM-introjected, EM-external regulation, and amotivation were measured by the Academic Motivation Scale (college version) (AMS). The AMS is a 28-question instrument with four scales per variable with a seven-point self-ranked Likert scale for each question.

Motivation has historically been measured as a single general motivation measure recognizing scores on a scale from unmotivated to motivated or as a tripartite score with a single value for external, internal, and amotivation (Moen & O'Doyle, 1978). However, Chemolli and Gagne (2014) suggested that SDT supports a more multidimensional representation as there was a substantial structure within items that is not explained by the primary factors. This multidimensional approach, comprised of several factors, is said to fall along a continuum of relative autonomy and motivation not tracked by the AMS (Howard & Gagne, 2017; Litalien et al., 2017; Ryan & Deci, 2000). While the single continuum structure of self-determination as employed by the AMS is disputed by Howard et al. (2020a) for its multidimensional tendencies, a continuum or blended interpretation is accepted by the majority of published work (Howard &

Gagne, 2017; Howard et al., 2018; Litalien et al., 2017). Still, over 1000 academic research projects have cited or used the AMS for its reliability and validity in measuring student motivation.

Historically, instruments designed to measure motivation are scaled questionnaires developed to measure distinct regulation types. These instruments include the self-regulation questionnaire (Ryan & Connell, 1989), the multidimensional work motivation scale (Gagne et al., 2015), the academic motivation scale (Vallerand et al., 1992), the behavioral regulation in exercise questionnaire (Lonsdale et al., 2008), the self-report scale of intrinsic versus extrinsic orientation (Harter, 1981), and the motivational orientation scale (Lepper et al., 2005). A meta-analysis testing the continuum structure of self-determined motivation was conducted by analyzing 486 samples which indicated that these scales can predict the regulation across the continuum but that the exact distance between each scale could not be pinpointed, once again solidifying "motivation" as ordinal data (Howard & Gagne, 2017). Additionally, research between student motivation and associated outcomes: academic achievement, persistence, well-being, goal orientation, and self-evaluation anchor the SDT initiative (Howard et al., 2021).

Finding an appropriate, valid, and reliable instrument is a cornerstone of quantitative research (Gall et al., 2007; Roni et al., 2020). The instrument used in this study was the academic motivation scale (AMS) (Vallerand et al., 1992). Based on a self-report scale developed in 1992 by a team of French researchers, namely the Echelle de Motivation en Education (EME), the AMS has a theoretical background in self-determination theory and was initially composed of 28 items subdivided into seven subscales (Vallerand et al., 1989). The seven subscales include the three types of intrinsic motivation (to know, to accomplish, and to experience stimulation), three types of extrinsic motivation (external, introjected, and identified regulation), and amotivation

(Vallerand et al., 1992). The purpose of the EME was to test the initial motivation levels of college students. Similarly, the translated instrument (the AMS) assessed the seven subscales of motivation of English-speaking students. Both the English and French forms of the scale yielded almost identical findings with respect to internal consistency, temporal stability, factorial structure, and construct validity (Vallerand et al., 1992; Vallerand et al., 1993). Data provided by this scale compared scales of motivation against the dependent variable: success. See Appendix A for the instrument and permission to use this instrument.

Initial assessment of the construct validity of the AMS was performed through three correlations: among the seven AMS subscales, between the AMS subscales and motivational antecedents, and between the AMS subscales and motivational consequence (Vallerand et al., 1993). The three intrinsic motivations showed the highest positive correlations among themselves (*r*'s of .58, .59, and .62) (Vallerand et al., 1993). Correlations among the seven subscales generally displayed a simplex pattern, but adjacent subscales showed higher correlations than subscales farther apart. Subscales on opposite ends of the continuum, like IM Know and Introjection, with a correlation of -.43, displayed more negative correlations than intermediate subscales (Vallerand et al., 1993). Recently, the AMS went through exploratory structural equation modeling to evaluate its construct validity to determine whether it was more in line with modern theoretical expectations than with confirmatory factor analysis (Guay et al., 2015).

Additionally, correlations between AMS subscales and a series of variables that are generally hypothesized to be motivational antecedents and variables thought to represent educational and psychological consequences were computed. These variables include perceived confidence, informational, autonomy supportive, impersonal, optimism in education, and self-actualization autonomy. Correlations with perceived competence matched the hypothesis of high correlation (**r**=.10, **r**=.20, and **r**=.25) with IM subscales and weaker correlations with the EM and amotivation subscales (**r**=.11, *r*=-0.01, r=.01, and *r*= -0.31). Optimism also met the hypothesized measure of having positive correlations with both IM and AM measures but a negative correlation with negative correlations. Hypotheses concluding that self-actualization would be positively correlated with IM scales, lesser so with the identification subscales, and negatively with the amotivation scales were confirmed with *r* values -.03, .24, .32, .27, 0.04, -.00, and -.32 (Vallerand et al., 1993).

The AMS has been declared valid as well as reliable. The internal consistency of the subscales was assessed with a Cronbach alpha where values for each subscale varied between .83 and .86, with the exception of the Identification subscale, which has an alpha value of .62 (Vallerand et al., 1992). Specifically, six of the seven subscales, including IM-stimulation $(\alpha = .86)$, IM-accomplishment $(\alpha = .85)$, IM-to Know $(\alpha = .84)$, introjected regulation $(\alpha = .84)$, external regulation $(\alpha = .83)$, and amotivation $(\alpha = .85)$ had internal consistencies across the alpha sample, the second pre-test sample, a post-test sample, and under test-retest conditions (Vallerand et al., 1992).

The AMS consists of 28 items where each of the seven subscales contains four items. Each subscale is assessed on a 7-point Likert scale ranging from “does not correspond at all” to “corresponds exactly.” Responses were as follows: does not correspond at all = 1, corresponds little = 2 or 3, corresponds moderately = 4, corresponds a lot 5 or 6, and corresponds exactly = 7. The AMS has elementary, high school, college, and other adaptations, but the “college version” was used for this research (Vallerand et al., 1989). The combined possible score on the AMS ranges from 28 to 196, where each subscale score ranges from four to 28. A key is provided within the instrument materials to code which questions indicate each subset, as each subset is scored individually (Vallerand et al., 1989).

The AMS and accompanying survey questions was distributed to respondents via an email as the initial and secondary recruitment letter. Since the information collected maintained anonymity, the consent document was linked to the letter, and no further action was needed. Students then filled out the survey online using a Qualtrics survey. When distributed, participants were given an overview of the questionnaire and how they should fill out each item by ranking the correspondence to the question: Why do you go to college? (Ayub, 2010; Litalien et al., 2017; Ratelle & Guay, 2007; Vallerand et al., 1989). The AMS takes under ten minutes to fill out. Then, the scores are calculated by hand or electronically by the researcher.

The AMS continues to be a valuable tool in the interests of academic motivation. The scale is the premier tool for measuring motivation at the high school and college levels (Corpus et al., 2022; Pleace & Nicholls, 2022; Toth-Kiraly, 2022). The scale has also been tweaked to measure the academic motivations of prisoners and other multidimensional career situations (Gagne et al., 2015; Manger et al., 2020). In relation to this study, the AMS has recently been utilized in studying the motivation to conduct research in academics for teaching-oriented universities in China and to compare college students' motivation trajectories before and during the Covid-19 pandemic (Corpus et al., 2022; Zhou et al., 2022).

In addition to the motivation instrument, demographic information such as age, sex, and program type was included to gather data on the remaining predictor variables: sex, program type, and whether the student is of traditional college age or not. Additionally, two statements using the same 7-point Likert scale were included in order to collect perceived success assignments. Responses to the first five questions as well as the corresponding motivation subscale scores were connected and analyzed for each participant. Still, all student information remained anonymous throughout the course of the project.

Procedures

The researcher obtained approval from the Institutional Review Board (IRB) at Liberty University. The approval letter is located in Appendix B. After the university agreed to participate in the study, the researcher approached each of the teachers facilitating online education courses at the undergraduate level from the Dean of the School of Education. Professors of the online courses were provided with details of the study and agreed to communicate with their students about participating in the study. The researcher ensured that a minimum of 66 students were surveyed and worked with whatever demographic breakdown was provided by the initial sample. To encourage students to participate in the study, the researcher requested that course instructors post a short introduction in their respective Canvas courses, the LMS used by the university, as an announcement. The IRB approved the recruitment letter for the teachers' introduction to the study (See Appendix C) in the form of an email. The introduction to the study included a basic description of the research to be conducted and invited students to participate in the confidential study by completing surveys. A second approved email also went out as a recruitment follow-up (Appendix D).

Qualtrics, the university-approved web-based survey software tool, was used in the survey process. A consent form provided participants with information regarding the study, including its voluntary nature. The consent form was linked to the course announcement for participants to view (see Appendix E). Since the survey results remained anonymous throughout the course of the research, the consent form did not require a signature. The students were notified that they could withdraw from the study at any point in the research process and that the results of the study might be published but that any identifying information would be excluded. The survey was administered the first week of the term and could be completed over three weeks. Additionally, course instructors released a reminder announcement one week before the end of the survey period to remind students to participate. The researcher then entered the data from each survey into the Statistical Package for the Social Sciences (SPSS). At all stages of data collection, all information remained anonymous. Data was stored securely in SPSS, and only the researcher had access to the records. The data will be retained for a period of five years after the completion of this research study.

Data Analysis

The data were analyzed using logistic regression. Logistic regression is the most suitable for this study because it determines the correlation between "a dichotomous criterion variable and a set of predictor variables" (DeMaris, 1995; Gall et al., 2007, p.354; Warner, 2013). Finally, the significance of the test was assessed by a chi-square test since chi-squared tests can determine whether research data in the form of frequency counts are distributed differently for different samples and whether they can be placed into two or more categories (Gall et al., 2007). This test asks, "how likely is it that an observed distribution is due to chance?" and is typically used for nominal variables (Patten & Newhart, 2017).

The data analysis investigated the research question. The analysis began with descriptive statistics, including summary statistics (means and standard deviations) and frequencies for the continuous variables intrinsic, extrinsic, and amotivation. Next, the researcher ran logistic regressions to see how accurately perceived success could be predicted from the motivation factors. Regression is a quantitative approach to data analysis that is simple, flexible, and offers predictive associations between variables (Patten & Newhart, 2017). The linear combination of factors, including the three intrinsic motivation scores, the three extrinsic motivation scores, amotivation score, sex, and traditional and non-traditional college-age students, are all predictor variables. Next, a check for multicollinearity occurred. This test searched for high intercorrelations among the predictor variables (Gall et al., 2007; Morgan et al., 2004).

The data obtained were entered into SPSS. SPSS is a popular statistical software suite for data management and advanced analysis (Green & Salkind, 2016). The analysis began with descriptive statistics for the continuous predictor variables. The analysis includes summary statistics (means and standard deviations) and frequencies which were tabulated and displayed through bar graphs. Next, logistic regressions were run to determine relationships between each of the predictor variable groups and the outcome variable: success. Since the null hypothesis will be rejected at the 95% confidence level, the significance was assessed by a chi-square distribution to determine whether the identified correlational relationships were statistically significant.

CHAPTER FOUR: FINDINGS

Overview

The purpose of this study was to determine if a student's perceived success in an online education course can be predicted from a combination of motivation factors and other demographic variables. The categorical independent variables were sex (male/female/other), age (18-24, 24+), and program type (online/blended). The ordinal predictor variables were intrinsic and extrinsic motivation as well as the subscales IM-to know, IM-toward accomplishment, IM-to experience stimulation, EM-identified, EM-introjected, EM-external regulation, and amotivation. The criterion variable was "perceived success," where "success" is defined as a score of 1 in our collapsed Likert self-report, and "unsuccessful" is receiving a collapsed Likert self-report of 0 for the two perceived success questions. A logistic regression was used to test the null hypothesis. The Findings section includes the research question, null hypothesis, data screening, descriptive statistics, assumption testing, and results.

Research Question(s)

RQ1: How accurately can perceived success in an e-learning course be predicted from a linear combination of motivation factors for education students?

Null Hypothesis

$H_0$1: There is no significant predictive relationship between the criterion variable "perceived success" and the linear combination of predictor variables (intrinsic motivation, extrinsic motivation, IM-to know, IM-toward accomplishment, IM-to experience stimulation, EM-identified, EM-introjected, EM-external regulation, amotivation, sex, age, and program type) for online pre-service teachers.

Data Screening

The researcher sorted the data and scanned for inconsistencies in each variable. No data errors or inconsistencies were identified. Extreme outliers are points that do not fit the regression model well. Casewise diagnostics were used to examine outliers, cases of standardized residuals greater than 2.5. No outliers were identified, as indicated in Table 1, so all data were retained.

Table 1

Casewise diagnostics

Casewise List[a]
a. The casewise plot is not produced because no outliers were found.

Descriptive Statistics

Descriptive statistics were obtained on each of the independent variables. The sample consisted of 68 participants. The participant statistics include student age, sex, and program type. The demographic participant statistics are summarized in Table 2.

Table 2

Demographic Characteristics of participants

Variable	Category	*n*	%
Age	18-24	20	29
	25+	48	71
Sex	M	10	15
	F	58	85
	O	0	0
Program Type	Online	68	100
	In-Person	0	0

Table 3 summarizes the descriptive statistics for the perceived success variable questions that were presented on a 7-point Likert scale. The scale has a range from 1-7 as follows:

1-Does not correspond at all.

2-Corresponds a little less

3-Corresponds a little

4-Corresponds moderately

5-Corresponds

6-Corresponds a lot

7-Corresponds exactly

However, the data was then re-organized using the Likert collapsing method shown in Figure 2 to dichotomize the results into:

0-Perceived unsuccessful

1-Perceived successful

Table 3

Dichotomized Success Variable Data

Variable	*Category*	N	%
Success	Unsuccessful	19	28%
	Successful	49	72%

The 28 questions from the AMS-C 28 were presented on a 7-point Likert scale. The same scale was used for the perceived success criteria questions. Each response was scored and grouped according to the AMS-C 28 conditions. Table 4 represents the mean and standard deviation for each question grouping on the AMS-C 28. The key for the groupings are: (IM1) Intrinsic Motivation-to know (2, 9, 16, 23), (IM2) Intrinsic Motivation-toward accomplishment (6, 13, 20, 27), (IM3) Intrinsic Motivation-to experience stimulation (4, 11, 18, 25), (EM1)

Extrinsic Motivation-identified regulation (3, 10, 17, 24), (EM2) Extrinsic Motivation-introjected regulation (7, 14, 21, 28), (EM3) Extrinsic Motivation-external regulation (1, 8, 15, 22), and amotivation (5, 12, 19, 26). Descriptive statistics for each subscale were calculated by adding scores and computing mean, standard deviation, median, and mode. The results are reported in Table 4 here.

Table 4

Descriptive statistics for each AMS-C 28 subscale

Question Nos	Subscale	$\bar{x}$ Mean	s Standard Deviation	Median	Mode
2, 9, 16, 23	IM-to-know	21.5882	4.53588	22	20
6, 13, 20, 27	IM-toward accomplishment	20.2794	5.88660	21	18
4, 11, 18, 25	IM-to experience stimulation	16.5882	6.52260	16.5	14
3, 10, 17, 24	EM-identified regulation	22.6618	4.36270	23	28
7, 14, 21, 28	EM-introjected regulation	21.1765	5.85889	22	28
1, 8, 15, 22	EM-external regulation	19.7941	5.60000	20.5	20
5, 12, 19, 26	Amotivation	5.8507	4.28971	4	4

Cronbach's alpha is a common measure of internal consistency or reliability. Cronbach's alpha is commonly used with survey instruments with Likert scale response forms like AMS-C 28. The survey questions in this study had a high level of internal consistency with a Cronbach's alpha of .860 for just an online survey. The items within each AMS-C 28 subscale should be fairly strongly correlated with each other because the items are intended to measure aspects of academic motivation (Brace, Kemp, & Snelgar, 2013; Fallon, 2019). Cronbach's Alpha for each of the AMS-C subscales in this study appear is the second column, "Alpha", of Table 5. The third column of Table 6 are the values Vallerand et al. (1992) found when validating the English version of the AMS scale.

Table 5

Cronbach alpha values

Motivation Subscale	Alpha-this study	Alpha-Vallerand et al., 1992
IM-to-know	.815	.84
IM-toward accomplishment	.821	.85
IM-to experience stimulation	.827	.86
EM-identified regulation	.844	.62
EM-introjected regulation	.808	.84
EM-external regulation	.849	.83
Amotivation	.895	.85

The subscale values vary from .808 (smallest) to .895 (largest) in this research study. These values are similar to those obtained by Vallerand et al. (1992) and are all in the good, nearly excellent range for internal consistency. The original values for the scale varied from .83 to .86, except for EM-identified regulation subscale, which had a value of .62 which is in the questionable range (Vallerand et al., 1992). There is adequate internal consistency between this research study and those obtained in the original study as all alpha levels came back .7 or higher.

Assumption Testing

Assumption of Linearity

Binary logistic regression requires a linear relationship between the independent variables and the logit transformation of the dependent variable. The Box-Tidwell approach was used to test this. The continuous independent variables each underwent a natural log transformation for the test. If the interaction term is statistically significant, the original continuous independent variable is not linearly related to the logit of the dependent variable therefore failing the assumption of linearity (Laerd Statistics, 2017). Here, the Bonferroni correction is applied to the terms in the model, assuming thirteen terms were tested. We take the original *p*-value (0.05) and divide it by the thirteen terms to get a new *p*-value of .004. The motivation and demographic variables were all linearly related, with $p \geq 0.04$ for all and a combined *p*-value $0.082 > 0.05$. The results are below in Table 6. Based on this assessment, all independent variables were found to be linearly related to the logit of the dependent variable. The assumption of linearity was tenable.

Table 6

Linearity Statistics

	Score	Sig.
IM-To Know	2.479	.115
IM- Toward Accomplishments	1.661	.198
IM-To Experience Stimulation	.559	.455
EM-Identified Regulation	6.488	.011
EM-Introjected Regulation	2.276	.131
EM-External Regulation	.844	.358
Amotivation	1.932	.164
IM1 by ln_IM1	2.491	.114
IM2 by ln_IM2	1.895	.169
IM3 by ln_IM3	.809	.368
EM1 by ln_EM1	6.882	.009
EM2 by lin_EM2	2.403	.121
EM3 by ln_EM3	.926	.336
Amotivation by ln_amotivation	1.527	.217
Overall Statistics	21.830	.082

Assumption of the Absence of Multicollinearity

A Variance Inflation Factor (VIF) test was conducted to ensure the absence of multicollinearity. This test was run because if an independent variable (x) is highly correlated with another independent variable (x), they essentially provide the same information about the dependent variable. The Tolerance level should be .100 or greater (Laerd, 2017). If the Variance Inflation Factor (VIF) is too high (greater than 10), then multicollinearity is present. Acceptable values are between 1 and 5. The absence of multicollinearity was met between the variables in this study, except for IM-to Know, which was just over five at 5.083. See Table 7 collinearity statistics.

Table 7

Collinearity Statistics

		Collinearity Statistics	
Model		Tolerance	VIF
1	Sex	.764	1.310
	Age	.806	1.240
	IM-To Know	.197	5.083
	IM-Toward Accomplishment	.201	4.974
	IM-To Experience Stimulation	.362	2.763
	EM-Identified Regulation	.536	1.867
	EM-Introjected Regulation	.234	4.275
	EM-External Regulation	.428	2.334
	Amotivation	.894	1.118

Note. The dependent variable is perceived success.

Inferential Statistics

To answer the research question, the data were analyzed using a binomial logistic regression to predict potential relationships between the independent variables and the single dependent variable: perceived success. This statistical analysis was appropriate at is investigates the research question. **RQ1:** How accurately can perceived success in an online course be predicted from a linear combination of motivation factors for education students? The dependent variable is binary and one of more of the independent variables were categorical (Hilbe, 2016; Warner, 2013). The following assumptions for the research question were met as shown above:

- The one dependent variable was dichotomous (perceived successful/ unsuccessful).
- One or more independent variables were nominal or categorical (sex/program type)
- Observations were independent, and the dependent/independent variables were mutually exclusive and exhaustive.
- A minimum of 15 cases per the independent variable “age” were met, although that criterion was not met for “sex” or “program type.”
- The continuous independent variables were tested for the assumption of linearity through the transformation of the logit function.
- There were no significant outliers.

Statistical Significance

The binomial logistic regression was conducted to determine whether students’ perceived success in online education courses can be predicted by age, sex, program type, or motivation levels. The logistic regression was run between the dependent variable: perceived success, and the independent variables: intrinsic motivation, extrinsic motivation, and amotivation as well as the motivation subcategories IM1, IM2, IM3, EM1, EM2, EM3. The regression also included the variables age and sex. It should be noted that there were only 10 subjects who identified as “male” rather than the necessary 15 and that program type was excluded from the calculations as there was no variability there. There was one standardized residual with a value of 2.350 standard deviations, which was kept in the analysis. The Hosmer and Lemeshow Test result in Table 8 shows that the test was not significantly significant, therefore indicating that the model was not a poor fit (Laerd Statistics, 2017).

Table 8

Hosmer and Lemeshow Test

Step	Chi-Square	df	Sig.
1	10.766	8	.215

The omnibus tests of model coefficients was run to test the overall statistical significance of the model. The results are outlined in Table 9, which shows that the test was not significantly significant at $p > .05$.

Table 9

Omnibus Tests of Model Coefficients

	Chi-Square	df	Sig.
Step	6.596	3	.086
Block	6.596	3	.086
Model	6.596	3	.086

Table 10 reveals that 16 to 23% of the variance is explained by Cox & Snell R^2 or Nagelkerke R^2.

Table 10

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
Step	68.418[a]	.158	.226

Note. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Binomial logistic regressions estimate the probability of an event occurring. If the estimated event occurring is greater than or equal to 0.5, the event is considered occurring, and if the probability is less than 0.5, the event is labeled as not occurring. This way, the logistic regression can predict whether a case can be correctly classified or predicted by the independent variables. With an overall percentage of 91.4, Table 11 shows that the addition of the independent variables improves the overall prediction of cases into their observed categories of the dependent variable. Table 11 shows the percentage accuracy classification (PAC) for the independent variables is 76.1%.

Table 11

Classification Table

		Predicted		
		Success		
	Observed	Unsuccessful	Successful	Percentage Correct
Step 1	Success	7	12	36.8
		4	44	91.7
	Overall Percentage			76.1

Note. The cut value is .500.

Table 11 also provides information on the regression's sensitivity, specificity, and positive and negative predictive values. For sensitivity, the model shows that 91.7% of students who were successful were also predicted to be successful by the model. As for specificity, 36.8% of students who reported they would not be successful were correctly predicted by the model not to be successful. The positive predictive value then is 78.6%. The negative predictive value is 63.6%.

Further, Table 12 reveals more detail about the individual variables in the analysis. The Wald test determines the statistical significance for each of the independent variables and used in conjunction with the Sig. values in the sixth column of Table 12. Of the ten predictor variables, the tests show that EM1 (Extrinsic Motivation-identified regulation) was statistically significant in the model ($p = .038$) but that none of the other predictor variables resulted in statistically significant results. Extrinsic motivation – identified regulation had 1.21 times higher odds of predicting student perceived success in an online education course than those in any other group.

Table 12

Variables in the Equation

		B	S. E.	Wald	df	Sig	Exp(B)	95% CI for EXP(B) Lower	Upper
Step 1[a]	Sex	-.180	1.017	.031	1	.859	.835	.114	6.128
	Age	-1.037	.766	1.834	1	.176	.354	.079	1.591
	Intrinsic	.045	.072	.390	1	.532	1.046	.908	1.204
	Extrinsic	.137	.102	1.805	1	.179	1.147	.939	1.401
	IM1	.144	.152	.894	1	.344	1.155	.857	1.556
	IM2	.009	.115	.006	1	.938	1.0009	.805	1.265
	IM3	-.076	.081	.868	1	.352	.927	.791	1.087
	EM1	.190	.106	.008	1	.038	1.209	1.010	1.448
	EM2	-.009	.106	.008	1	.930	.991	.805	1.219
	EM3	-.048	.079	.366	1	.545	.953	.817	1.113
	Amotivation	-.064	.067	.929	1	.335	.938	.823	1.069
	Constant	-1.618	2.267	.509	1	.475	.198		

Note. The variable(s) entered on step 1 were: enter your sex, please indicate your age range, IM1, IM2, IM3, EM1, EM2, EM3, intrinsic motivation, extrinsic motivation, amotivation.

Results

The research question is, "How accurately can perceived success in an online course be predicted from a linear combination of motivation factors for education students?" To address this question, the null hypothesis: there will be no significant predictive relationship between the criterion variable "perceived success" and the predictor variables (IM-to know, IM-toward accomplishment, IM-to experience, EM-identified, EM-introjected, EM-external regulation, amotivation, sex, age, and program type) for online pre-service teachers. The data were analyzed using a binomial logistic regression to address the research question to predict potential relationships between the predictor variables and the criterion variable.

This statistical analysis was appropriate as it investigated the relationship between the dichotomous criterion variable "success" and each of the independent predictor variables (Hilbe, 2016; Warner, 2013).

- The one dependent variable was dichotomous.
- One or more independent variables were nominal or categorical.
- The dependent variable and the independent variables were mutually exclusive and exhaustive.
- A minimum of 15 cases per independent variable was met for all variables but sex.
- There were no continuous independent variables.
- There was no multicollinearity, as shown in the VIF.
- There were no significant outliers.

Through the data analysis of the research question presented in this chapter, the researcher determined there was not enough evidence to reject the null hypotheses because the overall p-value was not significantly significant $p>0.5$. However, Extrinsic Motivation-identified regulation did have a significant effect on the model. Still, the remaining variables: sex, age, IM-to know, IM-toward accomplishment, IM-to experience stimulation, EM-introjected, EM-external regulation, intrinsic motivation, extrinsic motivation, and amotivation had no significant relationship. A further investigation and explanation of these findings will be discussed in Chapter Five.

CHAPTER FIVE: CONCLUSIONS

Overview

This chapter discusses the research project compared to the work mentioned in the literature review, provides implications on how the study will contribute to the field of research, recognizes the limitations of the current research study, and reveals recommendations for future research. This study aimed to determine whether perceived success in e-learning courses for pre-service teachers can be predicted by their Academic Motivation Scores on intrinsic, extrinsic, and amotivation scores as well as the sub-categories of motivation. The results and implications of the research project on motivation, e-learning, and pre-service teacher research are reported within.

Discussion

The purpose of this quantitative, predictive-correlational study was to investigate a predictive relationship between a student's level of intrinsic, extrinsic, and amotivation and their perceived success in an e-learning environment. Specifically, students perceived success in an online introductory education course was considered, as well as their age, sex, and program type. To explore the perceived relationship between the predictor variables IM (IM-to know, IM-towards accomplishment, IM-to experience stimulation), EM (EM-identified, EM-introjected, EM-external regulation), amotivation, sex, age, and program type with success in an e-learning course for pre-service undergraduate students, the following question was posed:

RQ1: How accurately can perceived success in an e-learning course be predicted from a linear combination of motivation factors for education students?

The data analysis suggests that the variables are not significant predictors of perceived success for our target population: online pre-service teachers enrolled in an online section of

EDUC 201 at a prominent southern university. The variables sex, age, and program type had no significance in the study. With no traditional, on-campus students enrolled in the online course, program type was removed as a variable. Additionally, sex and age were not significant predictors (p=.176; p=.859). While amotivation did correlate with “unsuccessful,” extrinsic motivation did not vary significantly from those with strong intrinsic motivation factors, as the research suggests (Fidalgo et al., 2020; Firat et al., 2018; Mahande & Akram, 2021). The only significant correlation is between EM-identified regulation (EM1) and success (p=.038).

Higher intrinsic and extrinsic motivation scores leaned toward perceived success in learning, consistent with recent e-learning and motivation studies (Eom, 2019; van der Beek et al., 2020). Although studies like Hongsuchon et al. (2022) specifically noted intrinsic motivation as the pre-requisite for successful e-learning, it was extrinsic motivation, an extrinsic subtype, that had the most significant impact on perceived success in the current study. Ryan et al. (2019) identified EM-identified regulation as an autonomous form of motivation that leads to positive outcomes according to societal expectations which does apply to the collegiate success formula.

This regulation makes sense in the context which Deci & Ryan (1985, 1991) and Vallerand et al., (1992) designated as school success: working hard, getting good grades, trying to get a job, and making more money. Fidalgo et al. (2020) stated that the principal reason students may not enroll in an online class is their challenge to stay motivated, but that the keys to staying motivated, according to Usher et al. (2021) are self-regulatory and autonomous techniques. EM-identified regulation is the most autonomous form of extrinsic motivation where the learner has identified the personal importance of their behaviors towards a course and can regulate their behaviors, attitudes, and performance in that course (Deci & Ryan, 1991). The importance of learner autonomy is further supported by TTD. According to the TOM, the perceived locus of causality of learning is shared between EM-identified regulation and IM-intrinsic regulation. The results of this study, viewed under these conditions, are consistent with the literature review, even if the original prediction was that an intrinsic motivation subscale would have been the most significant predictor of perceived success. For these reasons, EM-identified regulation is consistent with the 2023 online education student: responsible enough to work from home and stay motivated while still understanding that there is a beneficial outcome (graduation, career, personal satisfaction) as the ultimate outcome (Caruth, 2022).

As with so much in this technological generation, trends are changing yearly rather than over the course of decades like in the previous century. No two years of teaching look the same from a teacher's perspective, and students change year to year as well. Pre-pandemic studies (Fidalgo et al., 2020; Firat et al., 2018; McClean, 2020; Tang et al., 2020) should be held in sharp contrast to studies like Casey-Hayford et al. (2022) or Chan (2022). In the same regard, those studies could even be considered outdated today. The teacher shortage is propelled by two distinct groups: those leaving teaching due to exhaustion, low pay, and low respect, or low enrollment in EPPs among the current generation (Casely-Hayford et al., 2022; Chan et al., 2021a; Tang et al., 2020). Current economic trends and societal norms could shift student motivation from the luxuries of intrinsic learning to necessary, more extrinsic factors (Caruth, 2022).

EM-identified regulation is still an autonomous motivation factor and is, therefore, still consistent with the key ideas of SDT and SCT as described in the literature review. The intrinsic factors outlined by Pelikan et al. (2021) could have shifted only slightly to match that of EM-identified. In a post-pandemic educational setting, the conversation is still centered around student autonomy, completing assessments, and passing courses (Ali & Nath, 2022). This research implies that current students need that autonomous motivation shown in this study, but that there is a stronger pressure to pass assessments and courses than to absorb material, apply knowledge, or other more intrinsic actions than before (Ali & Nath, 2022).

Aside from motivation variables, the current study considered a predictive relationship between perceived success and age, sex, and program type as well. Since the survey took place during a summer course and one of the first courses in the EPP, all participants were online students, so that variable was excluded from the analysis. The participant pool did have both male and female students, students of traditional college age and those of more advanced ages. Contrary to Shillingford & Karlin (2013), there was no significant difference in the perceived success of either age group. However, Carreira & Lopes (2021) explain why many non-traditional college-age students participated in the study. While their sex may affect student self-efficacy (Chan, 2022; Tzu-Ling, 2019), we cannot conclude whether sex was a significant predictor of perceived success for pre-service online education students. With the small sample size, this variable could not be further explored.

The results of this study included EM-identified regulation having a significant predictive relationship with perceived success and that none of the remaining variables had a significant relationship. These findings are consistent with studies like Caruth, 2022; Carreira & Lopes, 2021), but inconsistent with other studies (Shillingford & Karlin, 2013; Firat et al., 2018, Pelikan et al., 2021). The current economic crisis, teaching shortage, and post-pandemic college student experience explain some of that variance. Other explanations for the inconsistent results are listed in the limitations and recommendations for future studies sections.

Implications

Prospective college students, counselors, administrators, university planners, and educators can benefit from the findings of this research project along with the existing and future data available in the field of pre-service teacher education and e-learning. By using this information, prospective college students can begin to evaluate their motivations for learning and school to determine if an online, blended, or traditional on-site program is best suited for them. Counselors, parents, and other stakeholders can also help guide prospective students in the right direction. Administrators and university planners can begin to curate online and in-person course catalogs to meet the specific needs of today's learners. Educators, specifically college professors, can add this content to their ever-evolving information bank on today's college students. This research solidifies one thing: predicting student success is a multifaceted and ever-changing challenge. The knowledge that e-learning is a permanent tool/platform in the education system that needs to be continuously explored and enhanced just as traditional platforms are constantly in need of adapting, updating, and maximizing any information that adds to the body of knowledge in the field of education is worth exploring.

The literature review established a gap in the research about the overlapping topics of motivation, EPP programs, and e-learning (Carreira & Lopes, 2021; Firat et al., 2018; Kirk, 2020; McClean et al., 2020). The lack of information on these three topics could be attributed to the complex nature of their intersection. EPP programs are widely researched, but when it comes to pulling data on distance learning, the body of research is clouded by pandemic-related information (Allen et al., 2020; Al-Maroof et al., 2021; Yakoleva, 2022). The topic of EPP programs and motivation is more straightforward with common themes of learner autonomy, competence, and lifestyle motivation factors (Casley-Hayford et al., 2022; Goldhaber et al., 2020; Tang et al., 2020). However, today's college student, including today's teacher candidate, is an ever-changing population and nearly impossible to categorize. The results of this study, while consistent with the confines of SDT in that an autonomous motivation significantly relates to perceived success, are also in contrast with what we know about intrinsic motivation. It is important for stakeholders to understand that the student, at this exact point in time, chose to take an online class and wants to be a teacher but is also motivated by political unrest, a looming recession, and an unsettled teacher's union. They may not have the luxury of intrinsic motivation.

Extrinsic Motivation-identified regulation is the most autonomous of the extrinsic motivators. This subset of extrinsic motivation explains when a person identifies the value of an activity itself and understands that it can lead to a positive outcome according to societal expectations (Ryan et al., 2019). Earlier, we recognized that the decision to go to college in the first place is often motivated by this type of regulation. Now that we know this motivation subtype is linked to success in an online teacher education program, we can encourage students to follow this path. Had there been the inverse realization, stakeholders would have requested that students reconsider this decision.

EM-identified regulation is a great motivation, but that does not make the others bad in contrast. More studies must be conducted to investigate further the relationship these motivation subscales have on perceived learner success. My suggestions for future research are listed later this chapter. Parents, teachers, and peers can now open dialogues with prospective students. They can start conversations on why this young person wants to go to college, why they want to become teachers, and why they want to take an online or blended course. Understanding one's motivation can lead to learner autonomy, ensure they are placed in a program that fits their needs, and lead to a higher perceived success rate and, later, more career and life satisfaction.

The results of this study are a great reminder of why people choose to go to college. Yes, teachers may have a higher intrinsic calling to help people, make an impact, and be lifelong learners, but for all their intrinsic motivations, what makes them feel successful in school is still motivated by external views. These views could include money, grades, or the satisfaction of getting an answer right. Today's students require jobs, they need money to navigate life, and flexible time to explore the world. Today's teacher candidates value their time, want to be prepared for their futures, and see value in their education. SDT recognizes that motivation runs on a scale and that people are not labeled one subtype or the others. If perceived college success relies heavily on these external factors, students and professors alike must be aware of this. This topic must continue to be explored and researched. This study helped close the gap in the research, but more is needed to narrow the gap further.

Limitations

A limitation of this study was the size of the sample. The researcher did not have direct access to the sample population and therefore had to rely on convenience sample methods to acquire participants. Since participants were asked to participate in a survey via email, the voluntary nature and length of the questionnaire led to low participation of only 68 completed surveys in two semesters. The survey was posted during both summer semesters of 2023, but could have reached more students if pushed during the regular school year or if it was integrated into the Canvas course. Next time, using more than one introductory course, collecting data throughout an entire year, and embedding the survey into the course materials should encourage more participants to volunteer. This initial limitation also led to a secondary limitation of uneven sample sizes across each of the predictor variables. All participants were online students, there were not any on-campus students who happened to be taking online courses over the summer as predicted. This did not affect the results of the study as no data was run on this variable. Further, data was run on sex as ten males and fifty-eight females responded, but this did not meet the minimum standard of males to full accurate information. If more students participated in a similar survey in the future, there might be more male students in general.

Another limitation of this study is that students were asked to evaluate their perception of success in online courses, but no actual success markers were collected. Because of the lack of access to the target population, students spoke of their attitude towards learning online and whether or not they thought they would succeed in courses like the one they were enrolled in. While perceived success is an important marker (Levesque-Bristol, 2020; Ryan &Connell, 1989), more objective success markers like course grade, assessment scores, and graduation rates also speak to the research question (Almarabeh, 2014). The results of this study may be more similar to Firat et al. (2018) if the research design addressed a final grade in an online education course rather than student-perceived success.

Finally, the quantitative nature of this study has its limitations. A qualitative or mixed-methods approach that opens the door to communication with these online pre-service teachers could add another layer to understanding how motivation can affect success in online courses for future educators. A longitudinal study that follows students through their undergraduate program, a two-group study that follows online and in-person teacher candidates, or even a discussion with the current participants could add to the understanding of how they perceive success.

Recommendations for Future Research

This study aimed to determine if a predictive relationship exists between a student's level of motivation, their sex, age, or program type and their perception of success in e-learning courses. The research was designed to assess a specific subset of students at a large Christian University: undergraduate pre-service education teachers enrolled in an online version of EDUC 201. The aim of the study was to add to the body of research regarding e-learning, teacher education, and motivation. The following list contains recommendations for further research to further the existing body of literature.

1. This study gathered quantitative motivation and demographic information on a limited number of students during a specific timeframe and population. Future research could open up the target population to include other courses, other universities, or to both online and in-person courses.
2. This study utilized a quantitative method to determine student motivation levels using the Academic Motivation Scale. Future studies could use a qualitative approach to interview prospective or current students to discuss their motivation towards pursuing a degree in teacher education. Qualitative methods could help pinpoint specific markers of perceived success beyond the variables within this study.
3. This study aimed to measure a student's perceived success in an online course. While perceived success is a great way to test how students feel about their education, more objective methods exist. Future research can aim to measure a student's motivation going into a course and then use their course grade, final exam grade, or a cumulative project to test the objective success of each student. Correlations can be drawn from those success criteria.

4. This study utilized the Academic Motivation Scale (College Version) as the motivation instrument. The AMC follows the theoretical constructs of SDT and SCT. An alternative instrument that follows the theoretical constructs of Maslow's theory of the hierarchy of needs, McClelland's achievement motivation theory, Hertzberg's two-factor theory, or another known theory of motivation could yield extremely different results.
5. This study found low survey completion and enrollment for students who were traditional on-campus students taking an online course over the summer. Furthermore, there were a limited number of students who identified as male who completed the survey. This led to their removal from statistical analysis. Future research should be conducted on these two underrepresented groups to understand further the impact their motivation levels have on their perceived success in online education classes.
6. This study took limited demographics, age and sex, into account. Future studies could look into race, ethnicity, religion, socio-economic, location, and more to see if certain markers contribute to perceived success in e-learning courses or if they effect the measured motivation levels.
7. This study could be replicated but designed with students from other disciplines. The population could be pulled from teacher education courses, health and medical services, business fields, the humanities, STEAM subjects, or other schools of thought. The study could also be replicated to include different levels of education, including high school, undergraduate, and graduate students all pursuing a career in education.

Summary

The findings from this study indicated that the academic motivation characteristics of online pre-service education students do not altogether have a significant relationship to their perceived success in online courses. However, a particular subcategory of extrinsic motivation, EM-identified regulation, does. According to the results of this study, there are differences between students who perceive their online learning to be successful and those who do not, mainly by those identified as amotivated or lacking motivation. The results also suggested that the most autonomous of the extrinsic motivators, EM-identified regulation is the most significant predictor of perceived success for online education courses. While the research suggests that intrinsic motivation would have been the stronger predictor, current climates and trends focus on completion and grades rather than fulfillment and satisfaction while still highlighting autonomy. Learner autonomy, after all, was the buzzword most often mentioned in e-learning success literature as well as EPP program requirements.

Since there is a current shortage of teachers and pre-service teachers enrolled in education programs, further research is necessary to draw further conclusions about the effect of motivation on success. As more and more schools continue to round out their online course catalogs and e-learning cements itself as a viable learning atmosphere, the combination of e-learning, teacher prep, and motivation should continue to be studied. Upon further research, institutions, advisors, teachers, and student stakeholders will benefit when considering a student’s options for college and beyond.

The current body of research on e-learning identifies the benefits of online education and the drawbacks. The question is no longer if online education works but how to optimize it. We can optimize that option if we can identify who learns best online. It could not be concluded that a student’s intrinsic, extrinsic, or amotivation level could predict this perceived success, which differs from pre-existing research on academic motivation. Further research, such as qualitative studies, larger sample populations, different instrumentation, alternative populations, and objective success measures, is necessary as it could add to the overall body of knowledge surrounding online preservice teacher education and motivation.

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APPENDIX

Appendix A- Instrument & Permission

AMS-College Version (Vallerand et al., 1992).

Survey Questions:

1. Indicate your sex: ☐male ☐female ☐other

2. Indicate your age: ☐18-24 ☐25+

3. Indicate your program type: ☐residential ☐online

For questions 4-5, indicate to what extent each of the following items presently corresponds to your experiences in this, or other, online courses.

Does not correspond at all		Corresponds a little		Corresponds moderately		Corresponds a lot		Corresponds exactly
1	2		3	4	5		6	7

4. I expect to earn good grades in courses I take online. 1 2 3 4 5 6 7

5. Online courses are effective and help me to improve my learning and understanding. 1 2 3 4 5 6 7

Appendix B- IRB Approval Letter

May 9, 2023

Erin Fleming
Kevin Struble

Re: IRB Exemption - IRB-FY22-23-1214 Measuring Motivation to Predict Perceived Success in e-Learning Courses for Pre-service Teachers: A Predictive-Correlational Study.

Dear Erin Fleming, Kevin Struble,

The Liberty University Institutional Review Board (IRB) has reviewed your application in accordance with the Office for Human Research Protections (OHRP) and Food and Drug Administration (FDA) regulations and finds your study to be exempt from further IRB review. This means you may begin your research with the data safeguarding methods mentioned in your approved application, and no further IRB oversight is required.

Your study falls under the following exemption category, which identifies specific situations in which human participants research is exempt from the policy set forth in 45 CFR 46:104(d):

Category 2.(i). Research that only includes interactions involving educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures, or observation of public behavior (including visual or auditory recording).
The information obtained is recorded by the investigator in such a manner that the identity of the human subjects cannot readily be ascertained, directly or through identifiers linked to the subjects.

Your stamped consent form(s) and final versions of your study documents can be found under the Attachments tab within the Submission Details section of your study on Cayuse IRB. Your stamped consent form(s) should be copied and used to gain the consent of your research participants. If you plan to provide your consent information electronically, the contents of the attached consent document(s) should be made available without alteration.

Please note that this exemption only applies to your current research application, and any modifications to your protocol must be reported to the Liberty University IRB for verification of continued exemption status. You may report these changes by completing a modification submission through your Cayuse IRB account.

If you have any questions about this exemption or need assistance in determining whether possible modifications to your protocol would change your exemption status, please email us at irb@liberty.edu.

Sincerely,
G. Michele Baker, PhD, CIP
Administrative Chair
Research Ethics Office

Appendix C- Recruitment Letter

Dear student,

As a graduate student in the School of Education at (…), I am conducting research as part of the requirements for a doctoral degree. My research aims to investigate a predictive relationship between a student's level of motivation along the academic motivation scale and their perceived success in e-learning environments, and I am writing to invite eligible participants to join my study.

Participants must be 18 years of age or older, (…), and be working towards an undergraduate degree in education. Participants, if willing, will be asked to complete a 30-point Likert Scale survey along with a few demographic questions. It should take under ten minutes to complete the procedures listed. Participation will be completely anonymous, and no personal, identifying information will be collected.

A consent document is provided as the first page of the survey. The consent document contains additional information about my research. After you have read the consent form, please click the link to proceed to the survey. Doing so will indicate that you have read the consent information and would like to take part in the survey.

To participate, please click here. I appreciate your participation.

Sincerely,

Appendix D- Recruitment Follow-Up

Dear student,

As a graduate student, I am conducting research as part of the requirements for a doctoral degree. My research aims to investigate a predictive relationship between a student's level of motivation along the academic motivation scale and their perceived success in e-learning environments. I am writing to invite eligible participants to join my study. Two weeks ago, a Canvas announcement was sent to you inviting you to participate in a research study. This follow-up announcement is being sent to remind you to complete the survey if you would like to participate and have not already done so. The deadline for participation is [Date Sunday of week 3 of the semester].

Participants must be 18 years of age or older, and be working towards an undergraduate degree in education. Participants, if willing, will be asked to complete a 30-point Likert Scale survey along with a few demographic questions. It should take under ten minutes to complete the procedures listed. Names and other identifying information will be requested as part of this study, but the information will remain confidential.

A consent document is provided as the first page of the survey. The consent document contains additional information about my research. After you have read the consent form, please click the link to proceed to the survey. Doing so will indicate that you have read the consent information and would like to take part in the survey.

To participate, please click here. I appreciate your participation.

Sincerely,

Appendix E- Consent Form

Consent

Title of the Project: Measuring Motivation to Predict Perceived Success in e-Learning Courses for Pre-service Teachers: A Predictive-Correlational Study.

Principal Investigator: Erin Fleming, Doctoral Candidate, School of Education, Liberty University.

Invitation to be Part of a Research Study

You are invited to participate in a research study. To participate, you must be 18 years of age or older, be a student of LU (either online or on-campus) and be working towards an undergraduate degree in education. Taking part in this research project is voluntary.

Please take time to read this entire form and ask questions before deciding whether to take part in this research.

What is the study about and why is it being done?

This study is about a student's motivation and perceived success in online education courses, and its purpose is to determine if a predictive relationship exists between the two. Motivation is measured on a taxonomy from strong internal motivators to external to not at all motivated, and success corresponds to how you perceive your success in online courses.

What will happen if you take part in this study?

If you agree to be in this study, I will ask you to do the following:

1. Complete a survey that will determine your motivation scores, perception of success, and demographic information including your age, sex, and program type. This should take under ten minutes.

How could you or others benefit from this study?

Participants should not expect to receive a direct benefit from taking part in this study.

Benefits to society include an addition to the body of literature surrounding student success, motivation, e-learning, and teacher education. This study could help advisors and counselors match students with programs, predict which class formats are best for them, and contribute to the overall success of a whole generation of college students.

What risks might you experience from being in this study?

The expected risks from participating in this study are minimal, which means they are equal to the risks you would encounter in everyday life.

How will personal information be protected?

The records of this study will be kept private. Research records will be stored securely, and only the researchers will have access to the records.

- Participant responses will be anonymous.
- Data will be stored on a password-locked computer. After five years, all electronic records will be deleted.

Is study participation voluntary?

Participation in this study is voluntary. Your decision on whether to participate will not affect your current or future relations with Liberty University. If you decide to participate, you are free to not answer any questions or withdraw prior to submitting the survey without affecting those relationships.

What should you do if you decide to withdraw from the study?

If you choose to withdraw from the study, please exit the survey and close your internet browser. Your responses will not be recorded or included in the study.

Whom do you contact if you have questions or concerns about the study?

The researcher conducting this study is Erin Fleming. You may a[redacted] now. If you have questions later, **you are encouraged** to contact her at [redacted] You may also contact the researcher's faculty sponsor, Dr. Kevin Struble, at [redacted]

Whom do you contact if you have questions about your rights as a research participant?

If you have any questions or concerns regarding this study and would like to talk to someone other than the researcher, **you are encouraged** to contact the IRB. Our physical address is Institutional Review Board, 1971 University Blvd., Green Hall Ste. 2845, Lynchburg, VA, 24515; our phone number is 434-592-5530, and our email address is irb@liberty.edu.

Disclaimer: The Institutional Review Board (IRB) is tasked with ensuring that human subjects research will be conducted in an ethical manner as defined and required by federal regulations. The topics covered and viewpoints expressed or alluded to by student and faculty researchers are those of the researchers and do not necessarily reflect the official policies or positions of Liberty University.

Your Consent

Before agreeing to be part of the research, please be sure that you understand what the study is about. You can print a copy of the document for your records. If you have any questions about the study later, you can contact the researcher using the information provided above.