EFFECT OF INTENSE SOCIAL MEDIA USE ON MIDDLE SCHOOL AT-RISK STUDENTS TEST SCORES IN SCIENCE AND MATH: AN ORDINAL LOGISTIC REGRESSION ANALYSIS

by

Terry Johnson

Liberty University

A Dissertation Presented in Partial Fulfillment

Of the Requirements for the Degree

Doctor of Philosophy

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ABSTRACT

The purpose of this quantitative correlational study was to investigate the intensity of social networking use, gender, and socioeconomic status as possible predictors of eighth grade at-risk middle school students' math and science test scores. Because this study hypothesized a general linear model between an ordinal response variable and more than one explanatory variables, ordinal logistic regression analysis was used. Social media is pervasive in the daily lives of students and so it can have a possible deleterious influence on student achievement. This idea continues to animate practitioners, researchers, parents, and all others interested in the achievement and success of adolescents. The current study was carried out in an urban middle school in the MidAtlantic United States. A convenience sample of 68 students participated in the study by completing a survey using the SNAIS instrument to measure their intensity of social networking use. A test of the full model (with gender, SES, and SNAIS as the predictor variables) compared with a constant-only or null model showed no significant effect. These outcomes were explored based on the data analysis results. Some reasons for this apparently contradictory result are explored in the discussion, including the need to examine more accurate results of student achievement versus self-reported measures to ascertain the extent of potential errors in estimating achievement levels. The study suggests that the possible outcome of the hypothesized relationship between social media, social networking, and academic achievement are more complex than might be assumed. Further research is required to investigate the relationship between the hypothesized variables.

Keywords: at-risk, benchmark assessment, reciprocal interactions, self-efficacy, social cognitive theory, social media, social networking sites, outcome expectancy.

Dedication

I dedicate this manuscript to my daughter Saniaa Johnson, also to my friends and family who have believed in my ability to accomplish this goal from the beginning and has continued to prove their confidence in me every day since.

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I would like to acknowledge the support and help of my dissertation committee member, Dr Ford for her insight, encouraging words, and constructive feedback. It is with great appreciation that I also acknowledge my chair, Dr. Savage. Thank you for challenging me to rethink my methods and for your contributions to my research. Thank you, Tiffany Baskerville, for supporting me along my journey and for understanding and listening to all my frustrations. Your affirming comments were of great encouragement, especially during the completion of my final manuscript. Finally, I need to be thankful for the support of those in my district who encouraged me and allowed me to use the district in my research. I am thankful to the students and parents who agreed to be represented in the statistical data of this study. They were the impetus behind this dissertation topic and I appreciate their participation.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

Social Cognitive Theory (SCT)

Socioeconomic Status (SES)

Social Networking Activity Intensity Scale (SNAIS)

Social Networking sites (SNSs)

CHAPTER ONE: INTRODUCTION

Overview

The purpose of this quantitative, predictive, non-experimental correlational study is to determine if a relationship exists between math and science test scores as measured by the benchmark assessment for middle school at-risk students and intensity of online social networking use as measured by the SNAIS instrument—while considering the possible role of gender and socioeconomic status. Chapter one provides a historical and social background of social networking use among children, also a theoretical framework for analysis. The problem statement examines the scope of the recent literature on this topic. The purpose of this study is followed by the significance of the current study. Finally, the research questions are introduced, and pertinent definitions are provided.

Background

Historical Overview

Historically, the ability to communicate and share information was dependent upon books, letters, phone calls, documents, and so on. Then, print media evolved into electronic media and eventually into digital media. Digital media of wide diffusion includes emails, digital audio and video recordings, eBooks, blogs, instant messaging, and—more recently—social media (Acerbi, 2016). Digital media advanced technology and the web, while the Internet and social media advanced the technology even further (Oggolder, 2012). As a result, social media and Social Networking sites (SNs) have become indispensable in modern-day society, and the influence on young people is significant. Social software development and free and open content came about in the late 2000s after the Internet became popular. The phenomena of user-generated data or content accelerated in 2005 with the introduction of Web 2.0 (Abbas et al., 2019). With this new phenomenon on the rise, the Web 2.0, or the Social Web, developed a broad new field of communication called social media. S*ocial media* is an online platform used to build social networks or social relations with other people who share similar personal or career interests, activities, backgrounds, or real-life connections (Akram & Kumar, 2017). These online platforms include websites and smartphone applications that enable users to communicate, create, and share content across geographical locations within these networks (Logghe et al., 2017).

Although social media, like bulletin boards and Internet chat, existed in the early 2000s, social networking gained most of its popularity between 2004 and 2006 after Facebook and Myspace were created (Acheaw & Larson, 2015). In the current years, social media websites like Facebook, YouTube, Instagram, Tik Tok, WhatsApp, Twitter, and Snapchat have become the most popular and widely used in the United States (Hawi & Samaha, 2017). Each of the major platforms (Facebook, Instagram, Twitter, YouTube, and Snapchat) have their own special functions, but they thrive on similar values or principles like popularity, hierarchical ranking, neutrality, quick growth, large traffic volumes, fast turnovers, and personalized recommendations (Dijck, 2013). Although it is apparent that SNs and their applications have evolved into an incomparable communication tool, social media use among teens conveys benefits as well as risks for this population (Wang et al., 2018).

Society-at-Large

At the beginning of 2021, there were 4.20 billion social media users around the world ("Digital 2021: Global Overview Report" 2021). This equates to more than 53% of the total global population spending on average of 48 hours per week online. The Global Web Index

(GWI) reports that in the United States, the average American now spends more time using their phone and engaging in social media activity than watching TV, but that may be because TV content can now be watched via streaming apps. While many adults have learned how to balance their time online with their day-to-day activities, the younger generation, the digital natives, have instead decided to multitask or task-switch (Alzahabi et al., 2017).

Social media has become one of the most influential Internet-based technology offerings used among young people in today's society. According to a Pew Research Center (2018) study on United States teens, 95% of teens reported having a smartphone or access to one, and 45% say they are online almost constantly. The study also reported that as smartphone access has become more prevalent, a growing number of teens now use social media on a near-constant basis. With the Internet drastically changing how students interact socially and learn, schools now perceive technology as essential to 21st-century education. This has led to research focused on the positive and adverse effects of social media use on students' learning behaviors. Studies have indicated some differences in teens' frequency of social media use by gender, demographics, and socioeconomic status (SES) (Akre et al., 2015; Herring & Kapidzic, 2015; Rideout & Robb, 2019). This study will extend the current body of literature on the relationship between academic achievement and intensity of social networking use (*i.e.*, how much time students spend on social networks based on specific activities through multiple types of platforms).

Current research revealed that social media use is correlated with lower overall academic performance, as measured by test scores and GPA (Apuke & Iyendo, 2017; Peter, 2015; Waqas et al., 2016). The unnecessary use of these sites also has an effect on reading habits and study time (Rafiq et al., 2019), physical health, mental health, motivation (Pang, 2018), selfconfidence, and self-esteem (Kaya & Bicen, 2016); all of which may produce a negative influence on learning performance. Due to the social effects of social media on attention and motivation, at-risk students are particularly susceptible to these negative influences. Smith (2011) defined at-risk students as students who experience a number of educational problems that lead to academic failure: they are transient, tend to have low socioeconomic status (SES), live in disadvantaged urban neighborhoods, display lack of interest in school, often have low standardized test scores, display a lack of interest in school, and represent non-native English speakers and minority groups. Bakken et al.'s (2017) study concluded that at-risk students fail to attain academic milestones in elementary school, and so they continue to underperform in subsequent years. Consequently, these students may experience grade repetition due to severe academic failure in middle school and in high school (Vinas-Forcade et al., 2020). Students placed at-risk in high school are in danger of failing to exit their education with the 21st century skills necessary for higher education, economic self-sufficiency, and civic engagement (Zaff et al., 2016). Therefore, for the purposes of this study, at-risk refers to those students with low SES, whose poor academic school results puts them at-risk of academic failure.

Research suggests that at-risk students are more likely to prematurely disengage from school than their more advantaged peers (Sanders et al., 2018). Therefore, there is a need to understand more about the factors associated with the disengagement of at-risk students. For instance, psychosocial and behavioral factors like conduct and attention have been linked to reduced rates of high school graduations (Sanders et al., 2018). Social media influences most students' psychosocial behavior, making them addictive psychologically, resulting in less attention being given to other activities, including school engagement, which leads to negative outcomes (Umar & Idris, 2018). Paying attention and concentrating on assignments is an important part of academic success (Anastopoulos & King, 2015); it depends on the students' ability to manage their time and the surrounding environment effectively to reach their academic goals (Kwon et al., 2018). Intense social media usage may negatively affect at-risk students who struggle with a positive home environment and managing their time.

According to Barton et al. (2018), most of the adverse effects of social media come from effort regulation. Students fail to self-regulate or self-manage their motivation and attention to elicit positive outcomes when challenged academically. Learning strategies such as regulation of time/study environment and effort regulation are vital to academic success as evidenced by their predictive power of grades and grade point average (GPA) (Barton et al., 2018). According to the social cognitive theory (SCT), people learn positive behaviors that they believe are beneficial to them by observing the benefits of other people exhibiting the same behaviors or positive reinforcement of people towards a specific behavior (Yoon & Tourassi, 2014). This human experience may offer new methods for educators to create social environments that facilitate learning.

Theoretical Background

This study examined the relationship between intense social networking use and middle school students' test scores in math and science. Albert Bandura's (1977) social cognitive theory (SCT) argued that a person's behavior is partially shaped and controlled by the influences of social networks (i.e., social systems) and the person's cognition (i.e., expectations, beliefs) (Bandura, 1989). This theory suggests that human behavior is formed through the reciprocal interaction between cognitive, behavioral, and environmental influences (Oluwatobi, 2020). Two key elements of the theory are self-efficacy and outcome expectations. Bandura emphasized self-efficacy and outcome expectation in developing human agency (McAlister et al., 2015; Rubenstein et al., 2018). He described human agency as a person's intentional acts and the core of self-development, adaptation, and self-renewal (Bandura, 2001). Social media tools may influence the behavior of students as they tend to imitate trends and get preoccupied with social identity (Ganda, 2014) and self-gratification (Larose et al., 2001), which often has a negative influence on their academics, leading to attention, memory, and motivation issues as stated by Bandura (1977). Thus, SCT suggests a theoretical framework to analyze how social media spread ideas and behaviors that can influence several psychosocial factors: motivation, mental health, and sleep disturbance.

Bandura highlighted that mass media influences individual behaviors, but the Internet has changed the nature of mass media. In today's society, social media has become one of the major forms of mass communication, disseminating messages widely, rapidly, and continuously to arouse meaning in large, diverse, and selective audiences (Defleur, 2010). Ross et al. (2016) described self-efficacy as the perception of one's ability to perform certain actions at the desired level. Self-efficacy can affect how students are behaviorally and motivationally active in their learning process. This idea can be used to establish principles to incorporate new ways of building attentional and motivational strategies to help students leverage social media's positive and adverse effects on learning.

According to social cognitive theory (SCT), people are more likely to engage in behaviors that they perceive to have positive outcomes or rewards than those they perceive to have adverse outcomes (Bandura, 1982). This idea was referred to as outcome expectation, which conveys, "beliefs about the likelihood of various outcomes that might result from the behaviors that a person might choose to perform" (McAlister et al., 2015, p. 172). Outcome expectation is different from self-efficacy in that it is more about the results that an action will bring, while self-efficacy focuses on one's ability to execute the action (Bandura, 2001).

Bandura (1986) defines outcome expectancy as the believed consequences of a person's prospective behavior, whereas self-efficacy is the perception of one's ability to perform certain actions at a desired level (Ross et al., 2016). Positive outcome expectancies have been found to be associated with a higher frequency of addictive behaviors among young people, which ties into excessive social media use and low academic achievement (Al-Yafi et al., 2018; Imani et al., 2018; Kim et al., 2017; Kumar et al., 2018; Upadhayay & Guragain, 2017). Self-efficacy is another prominent predictor of behaviors in the theoretical framework of the SCT because an individual will most likely carry out a specific behavior only if they determine that they are competent in putting it into practice (Wu et al., 2013). These subsets influence young adolescents' attitudes or behaviors and have a potential negative impact on academic outcomes. Self-efficacy and outcome expectation of students will be discussed in the theoretical framework in relation to their exercise of agency for mitigating the negative cognitive risk factors of intense social networking use.

Problem Statement

With more students connected to the Internet, social network applications have expanded from computers and laptops to mobile phones or tablets, increasing their influence on academic achievement. Sarwar et al. (2018) study revealed that social media serves as a dynamic tool to expedite the development of learning environments by encouraging cooperation and communication among students, reinforcing their learning behavior and performance. However, intense social media use can become problematic, placing them at academic risk due to media multi-tasking (May & Elder, 2018), poor study habits, and limited capacity for effort-regulation (Barton et al., 2018). Although some mixed results exist, many studies (Apuke & Iyendo, 2017; Azizi et al., 2019; Giunchigilia et al., 2018; Waqas et al., 2016) have explicitly revealed that intense social networking use can be problematic to students' academic achievement if caution is not exercised concerning its excessive usage.

To date, studies that have focused on the influence of social media and academics primarily used GPA as a measure. They also lacked diversity within the sample population. The participants predominately originated from university and secondary school settings in developing countries, with no data from other young students (Villanti et al., 2017). Research is needed to ascertain how intense social networking use predicts academic performance among younger students and even those in marginalized groups considered at-risk. Even though one may argue that intense social networking use can harm academic achievement, there remain gaps in the literature; therefore, generalizability is an issue. The problem is that the literature has not fully addressed how the intensity of online social networking use affects the academic achievement of young adolescents. This study aims to examine this issue within an urban middle school student population so that data related to an urban at-risk population can expand the literature (Villanti et al., 2017).

Purpose Statement

The purpose of this quantitative, non-experimental correlational study was to determine if a predictive relationship exists between intense online social networking use, gender, and socioeconomic status (SES) and the dependent variable—science and math test scores. The Social Networking Activity Intensity Scale (SNAIS) survey instrument (Li et al., 2016) will be utilized to measure intense online social networking use. The sample of participants derived from a Title I school district, in the mid-Atlantic region of the United States, with 82% of the student population economically disadvantaged (School Performance Report, 2020). The setting for the study was a middle school that serves grades 6-8; in 2021, they served approximately 780 students. Demographic data of the school district showed an ethnic distribution of 76.5% Black, 22.5% Hispanic, and 1% other race.

The independent variable, intense online social networking use, is defined as frequency and time spent on multiple types of online social media activities through multiple types of platforms (Li et al., 2016). The author noted that these social media activities included posting status updates, sending private messages, commenting on statuses, chatting, posting, tagging, or viewing photos and videos. The additional independent variables were demographic: SES and gender. Gender has an operational definition of male or female based on physiological/bodily aspects (*sex*) (the American Psychological Association refers to this aspect as ‘sex role’; APA, 2015). Aparicio-Martínez et al. (2020) suggested that personal characters play an important role in social media behavior, and gender difference may be a factor. Still, gender differences in social media use have not been clearly established despite the few studies highlighting an existing relationship between the two. Therefore, gender differences will also be investigated in this study to contribute to current research.

For the purpose of this study, SES is defined as a measure of capital (economic and social resources) accessible to the student, determined by the parent's education, occupation, and household income (He et al., 2020). This variable is represented in this study by economically disadvantaged students who qualify for free or reduced lunch. The use of eligibility for free or reduced lunch as a measure of a student's socioeconomic status continues to be a fixture of quantitative education research (Harwell & LeBeau, 2010). According to National Center for Education Statistics (NCES), despite its limitations, free/reduced price lunch eligibility is derived from the federal poverty level, and therefore highly related to it, and so the free/reduced price lunch percentage is useful to researchers from an analytic perspective as a proxy for SES

("NCES Blog," n.d.). The school district used in this study requires parents to fill out a lunch form to certify their child qualifies for free/reduced lunch. This form requires parents to answer questions relating to household income and size, government assistance, and contact information (see Appendix F). Students are eligible for a reduced price lunch if their household income is less than 185% of the federal poverty guide lines and for a free lunch if their household income is less than 130% of the poverty guidelines ("School Meal Trends," n.d.). Income eligibility guidelines for this school district and state is also provided in Appendix F.

Previous findings (Malak et al., 2017; Tekkant & Topaloglu, 2015) have shown a relationship between SES and social media addiction in undergraduates. This is supported by studies showing the effects of family SES on higher impulsivity and lower inhibitory control of social media use than high-SES individuals (He & Yin, 2016). In other words, individuals with low inhibition or high impulsivity have greater tendencies to overuse the Internet and social networks (SNs) (He et al., 2020). However, research focusing on the relationship between family SES and intense social networking use in young adolescence is still scant. This study used middle school students to represent this population and contribute to existing research. The criterion variables, math and science benchmark assessment test scores, are defined as formative assessments administered periodically throughout the school year, at specified times during a curriculum sequence, to evaluate students' knowledge and skills relative to an explicit set of longer-term learning goals (Herman et al., 2010). Benchmark assessments are used as a measure in numerous studies (Herman et al., 2010; Marzano, 2017; Mooney & Lastrapes, 2018; Paleologou et al., 2006; Snow et al., 2018).

Significance of the Study

Pew Research (2018) found that three online platforms other than Facebook (YouTube, Instagram, and Snapchat) are used by a large number of young adolescents ("Demographics and Statistics," 2020; "Social Media Use, 2018"). Since none of the previous studies in this area has focused on how intense online social networking use affects the academic achievement of at-risk adolescents, this study will be conducted in a middle school in the Mid-Atlantic region of the Northeastern United States, expanding the body of research to younger students (13 to 14 years of age). There is a need for more studies to validate and add to this research topic in different contexts and among different age groups.

By examining the at-risk group, parents and educators would identify the relationship between intense social networking use and academically at-risk students who have demonstrated weaknesses in their attentional and motivational skills. Theoretically, the SCT provided a framework to analyze how social media spread ideas and behaviors that can influence at-risk students' attention, motivation, and memory. This information can be used to remediate their study skills and learning strategies through tutoring, workshops, or modified coursework. Barton et al. (2018) suggested that providing students that struggle with self-regulated learning, better study skills, and learning strategies would help them succeed academically.

This study also underscored potentially significant benefits for young adolescents or middle school students as they learn to manage the problem of intense social networking use. Students in this age range constantly try to balance their attention, motivation, and time, while multi-tasking between social media activities and schoolwork. Moreover, this study will also benefit teachers, as it will provide potential means to obtain a clearer understanding of the relevant social-contextual factors that influence students' learning outcomes. This research suggests using social cognitive theory principles to elicit attention and motivational strategies to optimize learning for students. "Social media tools are a powerful and varied technology that need to be learnt by teachers for their ease of use and access, as well as for their low cost” (Doğan & Gülbahar, 2018, p. 223). This will inform educators and policy makers regarding how social media adds more value to the learning experience. Research conducted by Kent and Giles (2017) revealed that teacher preparation programs must integrate technology for pre-service teachers to gain experience in evaluating, selecting, and integrating technology in the curriculum.

Finally, this study provided information to parents about the link between social media use and academic performance. Knowledge of these findings can help inform parental decisions when it comes to the importance of monitoring their children’s social media usage.
This will allow them to provide positive opportunities and reduce the negative effects of these SNs. It can also influence when and how parents intervene to prevent possible addiction. Social networking addiction includes the characteristics such as ignoring the real problems of life, neglecting oneself, mood swings, concealing addictive behaviors, and mental health issues (Guedes et al., 2016). Social media addiction can also influence academic performance, as implicated by previous studies (Al-Menayes, 2015; Azizi et al., 2019; Das & Padmavathy, 2021).

Research Question(s)

RQ1: How accurately can middle school at-risk students’ *math* test scores be predicted from a linear combination of intense online social networking use, socioeconomic status (SES), and gender?

RQ2: How accurately can middle school at-risk students’ *science* test scores be predicted from a linear combination of intense online social networking use, socioeconomic status (SES), and gender?

Definitions

These terms are pertinent to the study:

1. *At-Risk*- students who experience a number of educational problems that lead to academic failure: they are transient, tend to have low socioeconomic status, live in disadvantaged urban neighborhoods, display lack of interest in school, often have low standardized test scores, and represent non-native English speakers and minority groups (Smith, 2011).
2. *Benchmark Assessment*- formative assessments administered periodically throughout the school year, at specified times during a curriculum sequence, to evaluate students' knowledge and skills relative to an explicit set of longer-term learning goals (Herman et al., 2010).
3. *Effort Regulation* - characterized by an individual's ability to persist during difficult tasks, putting forth the effort needed to complete the task, and not engaging in a more favorable task (Richardson et al., 2012).
4. *Gender* - operational definition, consisting of male or female based on physiological/bodily aspects (*sex*) (the American Psychological Association refers to this aspect as 'sex role'; APA, 2015).
5. *Outcome Expectancy* - the anticipated consequences, negative or positive, of a specific personal behavior (Bandura, 1986).
6. *Reciprocal Interactions* - posits that a person's behavior both influences and is influenced by personal factors and the social environment (Bandura, 1978).
7. *Self-Efficacy* - refers to the perception of one's ability to perform certain actions at a desired level (Ross et al., 2016).

8. *Social Cognitive Theory* - a learning theory stating that people learn by observing and imitating others and by positive reinforcement (Bandura, 1989).
9. *Social Media* - A social media is an online platform that people use to build social networks or social relations with other people who share similar personal or career interests, activities, backgrounds or real-life connections (Akram & Kumar, 2017).
10. *Social Networking sites* - A social aggregation that emerges from the Internet when sufficient numbers of individuals continue a public discussion for a certain amount of time, with sufficient human feeling, to form webs or connections of personal relationships in cyberspace (Hu et al., 2017).
11. *Socioeconomic status* - a measure of one's combined economic and social status (Baker, 2014).

CHAPTER TWO: LITERATURE REVIEW

Overview

The purpose of this literature review is to examine the relationship between math and science test scores as measured by the benchmark assessment for eighth-grade middle school at-risk students and intensity of online social networking use. The chapter opens with the theoretical framework. Bandura's social cognitive theory (SCT) frames the current study as it examines two personal motivators, outcome expectancies and self-efficacy through the triadic reciprocal model. The chapter then goes through a thorough review of the literature pertinent to social networking sites, and the role of gender and socioeconomic status in intense use. Review of the positive and negative influence of social networks on academic achievement completes the chapter, which ends with a summary.

Theoretical Framework

Social Cognitive Theory

Albert Bandura's (1986) social cognitive theory (SCT) provides the theoretical framework for this study. This theory presents a psychological perspective on human functioning that emphasizes the critical role played by the social environment on motivation, learning, and self-regulation (Schunk & Usher, 2019). To further explain this idea, Bandura formulated the construct *triadic reciprocality,* or *reciprocal interactions,* between three sets of influences: behavioral, environmental, and personal (Bandura, 1986). These factors all operate as determinants that influence each other. This literature review will use SCT to discuss how social media can influence academic achievement by highlighting the interactions among the triadic elements of school (social environmental), self-efficacy and outcome expectancy (personal), and intense social networking use (behavioral) factors as illustrated in Figure 1.

Much of the early psychological theorizing was founded on behavioristic principles that believed that human behavior was shaped and controlled automatically and mechanically by environmental stimuli, with no internal influences such as moods, thoughts, and feelings (Bandura, 2001). Albert Bandura, the renowned late psychologist, decided that his contributions to his field would fill this gap in research and challenge this perspective. Bandura (2001) believed that the advances in electronic technologies transformed the nature, reach, and loci of human influence. With the advent of the computer, new innovative thinkers emerged. People were considered agents of experiences rather than simply experiencers; therefore, the idea that people were hosts that only performed according to environmental influences became antiquated. Bandura proposed that people were human agents, and there were characteristics specific to humanity such as intentionality, forethought, reactiveness, self-reflectiveness, and self-efficacy. Though he agreed with learning theories like operant and classical conditioning, Bandura (1977) added that humans do not just undergo stimuli and responses. However, human behavior is learned from the environment through observational learning.

Albert Bandura developed the social cognitive theory (SCT) in 1986. He theorized that personal factors (e.g., cognitions, biology, affect, and self-efficacy) impact behaviors and environments (e.g., feedback, stimulation), and in turn, behavior and environment impact personal factors (Bandura, 1986; 1997; Schunk & Pajares, 2002). Bandura believed that people learn from their environment through observation and modeling. He hypothesized that for observational learning to occur, individuals must observe a model, cognitively retain what the model did, produce the modeled behavior, and be motivated to do so (Bandura, 1977). These motivated actions were contingent on expected positive consequences for performing the modeled actions. These *outcome expectancies*, which are cognitive beliefs, are developed through social interactions between models and observers (Schunk & Usher, 2019).

Social media is an influential source of observable behavior due to mediated social interactions and social presence, which qualifies it as a social environment. Social psychologist Schlenker (1980) defined social interaction as the awareness of the presence of others and subsequent adjustments in behavior in response to that awareness. Based on this definition, social media qualifies as mediated social interactions when synchronous with a higher social presence. Social presence is the degree to which media convey social cues, including nonverbal behavior and personally-identifying information or images, engendering a sense of relatedness or connection (Hall, 2016). This makes social networks or social media a strong influencer of individual behavior. Short message services (SMS), texting, and one-on-one chats (e.g., Facebook chat, Instagram direct messaging [DM]) all meet the conceptual definition of social interaction (Hall, 2016).

Bandura applied SCT to understand sociocognitive behaviors by analyzing how social networks influence new behaviors across the network (Yoon & Tourassi, 2014). Social networks have an influential role in society; therefore, understanding the psychosocial mechanisms through which symbolic communication influences human thought, affect, and action is essential (Bandura, 2001). Human thought, affect, and action refers to an individual's belief in his or her abilities and skills. This idea is linked to self-efficacy. Based on social cognitive theory, student goals for academic achievement are no longer solely based on environmental and personal factors. Rather, academic achievement is rooted in behavior that is perceived as an integral constituent of self-efficacy (action) and self-concept, a crucial and influential factor in closely associated with one's behaviors and various emotional and cognitive outcomes (Marsh & Martin, 2011). Self-efficacy and self-perceptions have reciprocal relations because they both focus on outcome expectations. However, self-efficacy is more focused on task-specific actions or a future perspective on how to change those actions (Schunk & Pajares, 2005). Self-perception influences one's actions, and it is mainly based on past occurrences. For this reason, this study will not expand upon self-perception and will only discuss self-efficacy as it relates to SCT and academics.

Outcome Expectancy

The social cognitive theory (SCT) encapsulates that outcome expectancy and self-efficacy are two significant determinants of behavior. People are more likely to engage in behaviors they anticipate to have positive outcomes or rewards than those they perceive otherwise (Bandura, 1982). Outcome expectancy is generally defined as the anticipated consequences, negative or positive, of specific personal behavior. In contrast, self-efficacy is the perception of one's ability to perform certain actions at the desired level (Ross et al., 2016). Self-efficacy and outcome expectancy are independent of each other and so will have independent effects on behavior change. Although outcome expectation has been found to contribute beyond self-efficacy to positive social media functions, it has not been a consistent predictor of positive academic outcomes (Lin et al., 2018). This is attributed to the fact that positive outcome expectancy can increase the intensity of social networking use, leading to addiction and problematic social media use.

Additionally, SCT suggests that social influence from the external environment or event provides information that can predict positive outcome expectancies that allow the individual to proceed with the behavior, developing an increase in future related behaviors (Bandura, 1969).

Thus, students who are situated in an environment that has easy access to social media, comes in constant contact with other frequent social media users who are inviting them to participate in social media activities, are more likely to develop positive outcome expectancies about its use; this will increase the chance of becoming addicted. Bandura (1986) later added to his earlier idea by concluding that outcome expectations predict behaviors, meaning that these expectations can affect the person's ultimate behavior using positive motivators or negative consequences that reduce motivation. When students are provided positive motivators for social media engagement, the behavior will increase, and the behavior will decrease when there are negative consequences.

The social cognitive theory is a framework to analyze how outcome expectancies can increase intense social networking use, resulting in higher addictive tendencies. The overuse of social networks (social media addiction) has positive and negative academic, social, and health consequences for students (Jha et al., 2016). Poor academic achievement is one of the most important negative consequences (Azizi et al., 2019). Several studies revealed that students who used social media more than average had a poor academic achievement and low level of concentration in the classroom (Al-Yafi et al., 2018; Imani et al., 2018; Kim et al., 2017; Kumar et al., 2018; Upadhayay & Guragain, 2017). Outcome expectancy is a cognitive risk that can negatively influence academic self-efficacy.

Conclusively, intense social networking use can become problematic for students and raises various physical, psychological, and social concerns in their daily lives. To avoid the psychosocial consequences it might cause to their motivation, mental health, and sleep pattern, students should be encouraged to control their time on social media and get involved in more cognitive activities. These cognitive activities include, among other things, posting views on a political or social issue on a blog and editing information in Wikipedia rather than simply scanning, watching, and reading content that others create (Khang et al., 2014). However, it is still difficult for students to monitor their thoughts, feelings, or addictive behaviors for social media as outcome expectancies increase in pleasure, self-satisfaction, or social recognition. In SCT, the outcome expectations generally consist of three primary forms such as physical effects (e.g., pleasure and discomfort), social effects (e.g., social recognition and applause), and self-evaluation effects (e.g., self-satisfaction) (Lin & Chang, 2018). Expected outcomes have been identified as a significant predictor of one's behavior (Bandura, 1986). This makes outcome expectancy a cognitive risk that negatively influences academic self-efficacy, as stated before. In understanding how self-efficacy influences academic achievement, it is necessary to review what constitutes the construct of academic self-efficacy.

Academic Self-Efficacy

One of the main objectives of this research is to increase understanding of the relationship between intense online social networking use and academic achievement outcomes. In doing so, this study will explore the potential mediating effects of academic self-efficacy to provide additional insight into how social media use may negatively influence behavior. A central premise of Bandura's SCT theory is that individuals strive for a sense of *agency*, or the belief that they can exert a large degree of influence over important events in their lives (Schunk & Usher, 2019). Central to this agentic perspective is individuals' *self-efficacy*, or their perceived capabilities to learn and perform actions at designated levels (Bandura, 1977a, Bandura, 1997). According to the SCT, self-efficacy is the essential characteristic influencing changes in human behavior (Yoon & Tourassi, 2014). Research shows that self-efficacy influences task choice, academic motivation, learning, resilience, effort, persistence, and achievement outcomes

(Bandura, 1997; Pajares, 1996; Schunk, 1995). It is also domain-specific, so different types of self-efficacy beliefs exist that relate to specific domains, including academic self-efficacy (Ansong et al., 2016).

Academic self-efficacy refers to individuals' convictions that they can successfully perform given academic tasks within a specific domain (e.g., subject area) by mastering motivational, cognitive, emotional, behavioral, and social resources (Richardson et al., 2012; Schunk, 1991). Academic self-efficacy employs self-regulation and other effective learning strategies that influence the perception of academic ability, which influences personal motivation for completing work and how well the student performs in school (Ansong et al., 2016). Therefore, it is widely recognized that academic self-efficacy is a significant predictor of academic achievement. Given the importance of self-efficacy for academic outcomes, a large body of research has focused on investigating differences in levels of self-reported self-efficacy for demographic groups defined by gender, age, grade, and levels of prior knowledge, even culture/countries (Nielsen et al., 2017).

Information for shaping self-efficacy beliefs comes from four primary sources: enactive mastery experience, vicarious experience, verbal persuasion, and physiological reactions (Bandura, 1986, 1997). Enactive mastery experience comes from successful past experience with the task, as Bandura (1997; Schunk, 1985) argued to be the most valid source of self-efficacy. This is likely due to the nature of self-evaluation. Within SCT, success or failure in mastery experiences will result in reevaluating self-efficacy and learning new skills (Bandura, 1997). Concerning vicarious experiences, parents who teach children ways to cope with difficulties and model persistence and effort strengthen children's self-efficacy. In addition, peers influence children's self-efficacy through model similarity; observing others succeed can raise observers' self-efficacy and motivate them to perform the task if they believe that they, too, will be successful (Schunk, 1987). If the model is a peer, the observer will likely believe she has similar abilities to the model and use it as a reference point for comparison (Bandura, 1997; Schunk & Pajares, 2002). Subsequently, if children observe the model failing to complete a task, they will likely believe they will fail the task as well, lowering their self-efficacy for that task even though they did not fail themselves.

Initial sources of verbal persuasion is centered on the family or a credible source. When children cannot make accurate self-evaluations, they may rely on others to convince them of their abilities. Persuasive communication and evaluative feedback may come from parents or teachers who are heavily invested in the children's cognitive development, and so they may spend more time with them on learning. However, social persuasions are more likely to contribute to inefficacy than inflated self-efficacy, such as interpreting discouragement from others as lacking capability (Aschbacher et al., 2010). Students' involvement and participation in school depend in part on how much the school environment contributes to their perceptions of autonomy and relatedness, which in turn influence self-efficacy and academic achievement (Pajares, 1996; Schunk, 1995). Heightened physiological reactions such as sweating, anxiety, fatigue, aches, and mood swings can affect the emotional state. Children may learn to mistake these arousals for incompetence, leading to inefficacious judgments, negatively affecting self-efficacy beliefs (Bandura, 1997).

Students with high academic self-efficacy achieve higher levels; they participate more readily in classroom activities, work harder, and persist longer when challenged. Self-efficacy regulates human functioning through cognitive, motivational, affective, and decisional processes (Benight & Bandura, 2004). Through these diverse means, belief in one's capacity to exercise a measure of control regarding social media use promotes resilience. Perceptions of one’s sense of self-efficacy can influence the activities pursued, situations in which he or she is willing to be involved, and the effort and time he or she is willing to expend on overcoming obstacles (Bandura, 1982). If a student who inspires to be *Instafamous* (a person with thousands of followers and likes on Instagram) and seeks social support from their Instagram followers but does not seem to acquire many likes, he or she may experience decreasing self-esteem or depression and increasing disinterest in his or her academic work and everyday activities.

Social media has changed the way students learn by influencing and shaping students’ perceptions and influencing learning engagement. With millions of students and teachers simultaneously active on social networks, it is significant to observe how the media could influence student-teacher classroom interactions and online communications (Mahmud et al., 2016). For example, there is a risk of low engagement in class if posts on social media (Kaya & Bicen, 2016) affect student mood. In addition, a pattern of social media absorption is likely to impair students' abilities or desires to remain engaged in important academic endeavors they may perceive as boring (Rosen et al., 2013). This will ultimately affect student performance, both currently and prospectively. A cycle of poor performance can contribute to student doubt concerning their own academic abilities and capacities, contributing to decreased perceptions of academic self-efficacy.

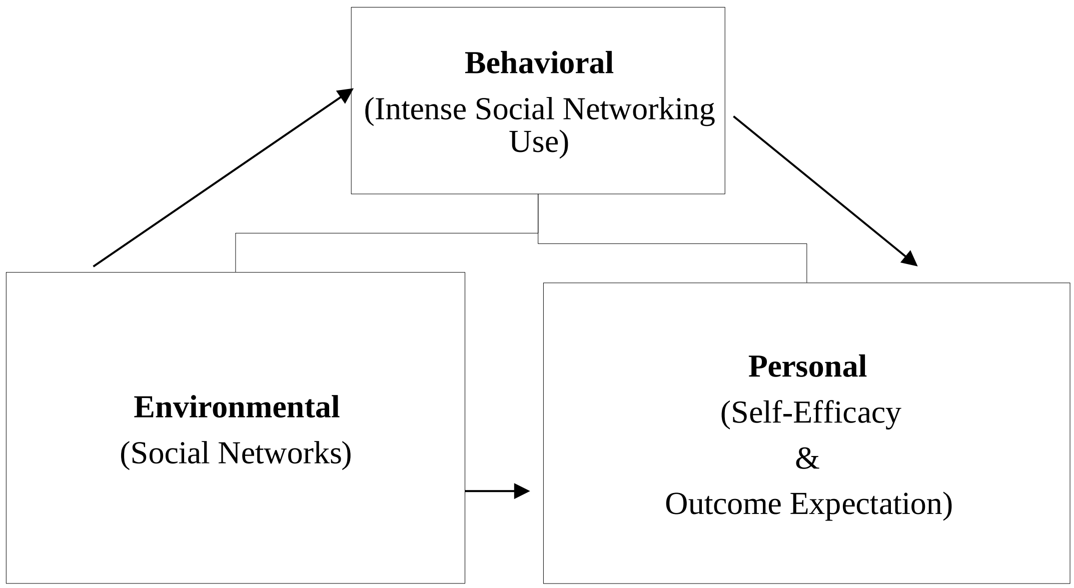
Another factor to consider is how gender affects academic self-efficacy. Studies have reported gender differences in academic self-efficacy regarding certain school subjects, such as science, language arts, or math (Else-Ques et al., 2010; Nielsen et al., 2017; Stewart et al., 2020). Huang’s (2013) meta-analysis of gender differences in academic self-efficacy found an overall gender difference in the level of academic self-efficacy, with males having the highest self-efficacy. Shoval et al. (2020) found a significant positive link between the sense of academic self-efficacy and academic achievement in both genders. A recommendation from Huang's (2013) meta-analysis was the need for future studies to look at the longitudinal viewpoint and examine gender differences in academic self-efficacy to determine the prevalence of gender differences during different life stages.

The social cognitive theory is a framework to analyze how academic self-efficacy can mediate the relationship between social media use and academic performance (Hassell & Sukalich, 2016). Social models provided by this social networking environment convey a significant amount of information about human values, styles of thinking, and behavior (Bandura, 2001). As a result, social media convey ideas and influence behaviors that can potentially undermine student academic success, but self-efficacy can mediate these effects. Individuals with higher self-efficacy commit to higher goals, engage in more complex tasks, persevere through challenges, and visualize success (Bandura, 1993). Self-efficacy is a cognitive risk that can negatively affect academic performance. This study will provide additional knowledge and insight into strategies to improve emotional, cognitive, or motivational processes to increase student learning and confidence. Teachers can influence academic self-efficacy through modeling using social media sites as an effective learning tool (Milošević et al., 2015). Accordingly, social media's capabilities and attributes can enhance learning and education when those tools are used for specific objectives and learning (Hassell & Sukalich, 2016).

Reciprocal Interactions

Figure 1

Triadic model in SCT. The arrows implicate the directions for the interest of this study



Although the SCT suggested bidirectional and reciprocal relationships among the three determinants in the triadic model, this study did not explore the reverse directions. In the Triadic Model (Figure 1.), the social networking environment, self-efficacy, outcome expectancy, and intense social networking use all interact to influence students' human functioning (cognition, motivation, and behavior), which ultimately impacts students' academic achievement. Each set of influences on human functioning affects the others and is in turn affected by them (Schunk & Usher, 2019). An individual's personal beliefs can affect their actions and environments, actions can alter someone's beliefs and environments, and environments can influence individuals' beliefs and actions.

In this model, internal and external influences affect motivational processes or personal influences (i.e., self-efficacy, outcome expectations). Personal influences include cognitions, beliefs, perceptions, and emotions (Schunk & Usher, 2019), and each process helps to sustain motivational outcomes. For example, positive outcome expectancy is a personal influence associated with higher frequencies of problematic social media use (Andreassen, 2015). In other words, social media use is generally reinforced by positive outcomes, such as feelings of social well-being in relation to others and positive mental health (Bekalu et al., 2019). Therefore, students are more motivated to use social media, increasing their intensity of use (behavioral). Moreover, people generally expect positive functions from their social networks (environment), including communication, socialization, entertainment, information, and developing social identity (Dunne et al., 2010). Bekalu et al. (2019) hypothesized that those who expect more positive outcomes from using SNs tend to spend more time on the sites, especially with the advent of smartphones, and so report higher addictive tendencies.

Personal Influence Factor

Self-efficacy is a key personal influence factor that can affect motivational outcomes, much like outcome expectancy. Learners who feel like successful learners are apt to engage in cognitive and behavioral activities that improve their learning, such as setting goals, using effective learning strategies, monitoring and evaluating their goal progress, and creating effective physical and social environments for learning (Schunk & DiBenedetto, 2016). In turn, self-efficacy can be affected by the outcomes of actions such as intense social media use due to environmental inputs (e.g., social comparisons with peers, social anxiety, etc.). These outcomes influence self-efficacy and continued motivation.

Students do not automatically develop self-efficacy. They develop a belief that they are making progress by observing a successful performance or completing a successful activity themselves, through persuasive feedback from others, and feeling less anxious in a situation.

This progress substantiates their self-efficacy, which enhances motivational outcomes (Schunk & DiBenedetto, 2016; Schunk & Usher, 2019). Research evidence shows that students use multiple sources when forming self-efficacy beliefs (Usher et al., 2019). In addition, extensive literature shows that self-efficacy influences one's choice of activities, effort, persistence, achievement, and self-regulation (Bandura, 1997; Honicke & Broadbent, 2016; Schunk & Usher, 2019). Self-efficacy interacts with another motivational process outcome expectancy to influence students' behavior on social media. One of the biggest impacts of social media on self-efficacy is social comparisons, people's biological inclination to evaluate their situation, skill, and overall identity in comparison to others, based on the information they receive about others (Jiang & Ngien, 2020). This is derived from perceived similarity between model and observer, which can serve as a source of information for determining behavioral appropriateness, forming outcome expectations, and assessing one's self-efficacy (Schunk & DiBenedetto, 2016). Also, it is important to add that social comparisons may not be effortful, meaning that female viewers may process stimuli unconsciously (Want, 2016).

Environmental Factor

Social comparisons can affect motivational outcomes (Schunk & Usher, 2019). However, this belief is two-fold. Learners who observe models they believe have greater similarities to themselves perform certain tasks successfully may compare themselves and believe that they also can be successful (observational learning/modeling [Bandura, 1977]). This belief may raise their self-efficacy and lead them to set goals, put forth effort, persist, and engage in other motivated behaviors. On the other hand, learners who observe others fail whom they believe are similar to themselves through comparison may also experience lower self-efficacy, which is a key personal influence on motivational outcomes (Schunk & DiBenedetto, 2016). Furthermore, comparisons to others who are perceived as better in a particular aspect might increase social anxiety. This is particularly applicable to the social networking environment. Social media generates ubiquitous comparison information and accessible feedback, such as the number of followers, likes, comments, and retweets (Jiang & Ngien, 2020). Young adolescents use this information to form impressions quickly. For example, students who believe they rank lower than others on social media can increase mental access to negative self-assessment and self-imagery during interactions with other people, resulting in more significant social anxiety (Stein, 2015) and low self-esteem (Fatima et al., 2017). This may lower self-efficacy. Social comparisons can also lead to students shaping positive behaviors to conform to specific standards or norms (Jiang & Ngien, 2020).

Environmental influences—such as socially modeled influences—can affect learners' motivational processes and outcomes (Wang et al., 2019). As mentioned before, observing a similar peer successfully perform a task (environmental influence) can raise observers' self-efficacy (personal process) because they may believe that if the model can learn, they can as well (Schunk, 2012). Other environmental influences in curriculum and instruction can influence learners' personal processes and motivational outcomes (Schunk & Usher, 2019). For instance, teachers utilizing social media as an instructional tool can engage and enlighten learners, which in turn can affect their motivational processes and learning.

Although studies establish a relationship between social comparisons and self-efficacy (Schunk & DiBenedetto, 2016, Schunk & Usher, 2019), more social cognitive research is needed using social media as a positive motivator. There has been little established about what types of social media variables are effective, how comparisons on social media affects students, and how social media's innovative communication may influence motivation. However, there are implications for teaching and learning. This study explores social cognitive principles incorporated in instruction to increase classroom engagement and improve learning outcomes.

Behavior

Personal influences like self-efficacy and outcome expectancy interact with the social networking environment to influence the discussed behavior, intense social media use. As active agents, we influence outcomes, act upon others' behavior, and coordinate behaviors with each other (Bandura, 2006). According to Schunk and DiBenedetto (2016), vital behavioral influences on motivational outcomes (personal influences) are choice of activities, effort, persistence, achievement, and environmental regulation. In this case, intense social networking use would be the behavioral influence on the choice of activities, effort (determined attempt at schoolwork), persistence (working through complex tasks), achievement (academic grades), and environmental regulation (productive management of time). Compared with learners with lower motivation (lower self-efficacy), those more motivated to succeed would be influenced positively by these factors, which helps to maintain motivational outcomes (Usher & Schunk, 2018). Based on the literature, self-efficacy and outcome expectations both are predictors of achievement due to their motivational outcomes, but self-efficacy is the stronger predictor.

Related Literature

While a social-cognitive approach to intense social networking use will explicate how and why individuals acquire and maintain certain behaviors, other individual-level variables will further explain its use's negative and positive effects. A distinctive feature of social cognitive theory (SCT) emphasizes social influence and the importance of external and internal social reinforcement. According to SCT, people are more likely to engage in behaviors that they perceive to have positive outcomes or rewards than those that they perceive otherwise (Bandura, 1982). An individual's past experiences influence outcome expectations, which predicts whether a person will engage in a specific behavior. This cognitive process affects self-efficacy or academic self-efficacy, the level of a person's confidence in his or her ability to perform an academic task (Bandura 1997) successfully. Self-efficacy beliefs influence four major psychological processes: regulating one's motivation, thought processes, affective states, or environmental conditions (Bandura, 1997). Drawing from these processes, the literature will examine the psychosocial factors of motivation, mental health, and sleep disturbance and their effect on academic performance.

Social Influence and Social Media

Social influence can relate to many aspects of society. In this paper, social influence is discussed in terms of SCT, how individuals change their behavior to meet the demands of their social networks. These networks emerge from the Internet when sufficient numbers of individuals continue a public discussion for a certain amount of time, with sufficient human feeling, to form webs or connections of personal relationships in cyberspace (Hu et al., 2017). Social media originated from these social networks and is now one of its biggest communication channels. According to Akram and Kumar (2017), social media is a multi-platform web-based form of data communication, allowing users to have conversations, share information and create web content. Junco et al. (2010) also defined it as a collection of Internet websites, services, and practices that support collaboration, community building, participation, and sharing.

Due to the prevalence of the Internet and the development of mobile technology, global audiences are spending more time on social media. Social media reaches about 4.20 billion users around the world ("Digital 2021; Global Overview Report," 2021), with as many as 71% of adolescents accessing more than one platform and approximately 24% of all adolescents admitting to being constantly online via smartphones due to increased mobile accessibility (Lenhart et al., 2015). New trends, such as social media addiction, are concerning to society because individuals can access social media more frequently from portable devices, such as computer tablets or cellular phones, compared with the past (He et al., 2020). The use of social media has become ubiquitous, with 73% of all American adults using social networking sites and significantly greater numbers of young adults and females contributing (Smith, 2014). Individuals use social media for various purposes: to pass the time, maintain relationships, meet new people, keep up with current trends, and gather social information (Kelly Quinn, 2016). It has become a cultural staple exerting a significant influence on the sociological structures.

Social media influences society by shaping politics, business, world culture, education, careers, innovation, and more. Individuals now employ social media as a means of mass communication and to share social, ethical, environmental, and political views. With social media at the forefront of the modern media context, citizens are exposed to news and remain digitally literate through their peers and social networks (Gil de Zúñiga et al., 2017). This has shifted the balance of power to the masses, bringing about more activism, racial and social injustice awareness, and engaging voters. Via social media, get-out-the-vote campaigns can provide significant information and endorsements promulgated through entire campaigns to young voters, increasing their participation (Ohme et al., 2019).

Social media tremendously affects commerce, allowing businesses to gain visibility, generate insights, stimulate demand, and create targeted product offerings. Companies are implementing viral marketing strategies on social media platforms to transmit to millions of people at a low cost. This strategy interrupts consumers during their online activities, creating a digital “hype” to promote products/services (Gunawan & Huarng, 2015). It also affects recruitment and hiring. According to a national survey conducted by CareerBuilder (2018) with a representative sample of more than 1,000 hiring managers, 70% of employers use social networking sites to research job candidates. Research supports the idea that social media has affected social norms and culture (Al-Sharq et al., 2015; Chukwuere & Chukwuere, 2017; Hashim & Kutbi, 2015; Tang et al., 2020; Taskin, 2017). Cultural norms affect student thought processes, making it an influential factor in their self-regulated learning process (Balakrishnan et al., 2016). Social media certainly influences daily life among modern students (Rajeev, 2015), and they are more likely to become addicted to social media (Simsek et al., 2019). This potentially leads to a change in their social, academic, and personal lifestyle. This study seeks to investigate social media's impact on valued outcomes such as academic achievement.

Gender Differences in Social Media Use

Gender is a standard investigation variable in technology-related research with identified differences in engagement style, frequency, and duration of digital media use among boys and girls (McFarlane et al., 2000). In this study, the term gender has an operational definition of male or female based on physiological/bodily aspects (*sex*) (the American Psychological Association refers to this aspect as 'sex role'; APA, 2015). Gender differences and some similarities are apparent in social media site preferences and amount of use (Herring & Kapidzic, 2015). Gender is also an essential factor concerning access to technology and in respect of the nature of engagement with a specific device. Social media data also show that males and females communicate very differently on social platforms. They each post different content, prefer specific platforms, and even use language differently ("Gender and Social Media," 2016).

A national survey study conducted by Common Sense Media (2015) of children eight to eighteen years of age found that girls spend 18% more time than boys on social networking sites and use them more actively than boys (Rideout & Robb, 2019). This was one of the most recent and significant studies conducted to explore gender differences. However, other studies (Lenhart et al., 2007; Rideout et al., 2010) show that boys spend more time on social media, depending on the activity. A recent study conducted by Rücker et al. (2015) showed inconsistencies. The possible explanation concerns socioeconomic issues and cross-cultural differences (He et al., 2020). In this study, exploring gender differences can reveal how frequently middle school adolescents (girls and boys) use SM sites and whether or not they engage in different or overlapping activities on these sites. It can also provide implications about the relationship between boys' and girls' time on social media.

Socioeconomic Differences in Social Media Use

There are important reasons for examining media use in terms of socioeconomic status and demographics. These include understanding how best to provide educational content or health messages, informing research examining possible differential effects of media use, and informing public policies on these issues (Rideout & Robb, 2019). There is increasing evidence that families originating from lower socioeconomic statuses (SES) is not only a social issue but also is a potential precursor to social media (SM) and other technological additions (He et al., 2020). In the United States, SES is a multifaceted concept measured via several variables: parent education, family income, employment status, and race or ethnicity, and these factors often overlap (Oyeboade, 2017). Families with lower parental educational levels are also more likely to earn less income, much like historically disadvantaged socioeconomic groups. Researchers found that teens from lower-income families spend more time with media than those from higher-income homes, a difference of two hours and 45 minutes a day on average (Rideout & Robb, 2019). The literature reveals a relationship between students' socioeconomic statuses, gender, and intense social networking use (He et al., 2020; Malak et al., 2017; Oyeboade, 2017; Tekkant & Topaloglu, 2015).

People from different socioeconomic statuses tend to project differing attitudes towards technology usage (Van Deursen & Van Dijk, 2014). Rideout and Robb (2019) found that 43% of white teens vs. 28% of black teens and 29% of Hispanic teens use a computer on a typical day for something other than school-related work. The authors concluded that white teens and those from higher SES groups are more likely to use a computer for Internet news, job searches, acquisition of product information, and schoolwork (Rideout & Robb, 2019). However, those from groups earning less income are more inclined to use the Internet for entertainment, social networking, and downloading content (Khan et al., 2016). Drawing on the data from the national survey conducted by Common Sense Media (2015), teens from families who earn less income and students of color who view screen media expend more time performing these actions than do their peers, with the most significant differences defined by family income (Rideout & Robb, 2019). This implies that SES may greatly influence online addictive behavior, but research in this area is still scant, so more extensive scholarship is needed.

Positive Influence of Social Media on Academic Achievement

Considering the intense social networking use among children and adolescents, there is an expectation that the frequency of using multiple types of online social networking activities can influence academic performance and the perception of social support (Leung, 2015). Social media tools can promote learning in more relevant and meaningful ways. More research in this area has revealed that social media can positively influence education (Al-Rahmi & Othman, 2013; Doğan & Gülbahar, 2018; Karvounidis et al., 2014; Sobaih et al., 2016). Social media can serve as a cost-efficient tool for educators while supplementing and augmenting the delivery of course material and the development of critical intellectual skills (Abe & Jordan, 2013).

Social Media as a Learning Tool

Akram and Kumar (2017) stated that social media provides an easy and effective method for students to share knowledge, and teachers can adopt its benefits to gain positive academic results. Sobaih et al. (2016) found that social media can potentially benefit teaching and learning, but it is under-utilized by most faculties. Therefore, educators need to adopt innovative methods and modernize lessons to engage students by utilizing social media as a learning tool in the curriculum to be career and college-ready. Teachers are a vital facet of accomplishing this goal. "Social media tools are a powerful and varied technology that need to be learnt by pre-service teachers for their ease of use and access, as well as for their low cost" (Doğan & Gülbahar, 2018, p. 223). Teacher preparation programs must integrate technology for pre-service teachers to gain experience in the evaluation, selection, and integration of technology in the curriculum (Kent & Giles, 2017); since it accelerates learning and has many advantages for special education students (Luo & Yang, 2016; Olakanmi et al., 2020).

Students should be appropriately instructed to use social media to achieve the best learning outcomes for effective social media integration into the curriculum. It should be integrated into the curriculum in an informative manner to support the content (Abe & Jordan, 2013). For example, playing a Tik Tok video in class to entertain students or to keep them quiet is not the same effective use as playing a Tik Tok video explaining natural selection to support audiovisual learners while improving engagement. Mbatha (2014) reported results that Web 2.0 tools play a pivotal role in opening learning avenues and increasing the communication and interaction opportunities for open and distance learning. Sobaih et al.'s (2016) study revealed that social media has an excellent value for academic-related purposes, particularly teaching and learning. Other studies reported positive effects on teaching and learning using social media (Irwin et al., 2012; Junco, 2012; Karvounidis et al., 2014). Despite the educational benefits of social media in teaching and learning, the levels of adoption for professional and teaching purposes trail behind personal use (Mbatha, 2014).

Student Engagement and Academic Achievement

Junco et al. (2012) defined student engagement as the amount of time and effort students invest in educational activities connected to learning outcomes. Social media integration enhances student engagement, resulting in positive academic outcomes (Alshuaibi et al., 2018). To mitigate the negative effects of social media, all students should be actively engaged or become active participants in school, responding effectively to the curriculum and enjoying learning experiences at school (Quin, 2016). Past studies revealed that social media integration enhances active learning (Ainin et al., 2015; Dyson et al., 2015; Junco et al., 2012). Through social media, students can share, discuss, and collaborate, which leads to enhanced and meaningful learning experiences in the classroom (Tur & Marín, 2015). According to Neier and Zayer (2015), social media should be perceived as an educational tool that can engage students in open discussion, promote seeking expression of their ideas both in and out of the classroom, ultimately promoting higher-level thinking. This allows students to become active learners by communicating, collaborating, interacting, and academically engaging with their peers more through these platforms (Alshuaibi et al., 2018).

Social media engagement on platforms such as Facebook, Instagram, Snapchat, and WhatsApp has become one of adolescents' most popular leisure activities (Van den Eijnden et al., 2021). Intense social networking use can affect psychosocial factors like mental health, motivation, and sleep disturbance, affecting academic achievement. Understanding the risk factors for intense social networking use is vital to advancing research and strategies to mitigate these effects.

Effects of Social Media on Mental Health

The mental health of schoolchildren is considered a prerequisite for several outcomes, including academic achievement. Though this study will not explore these variables, mental health will be examined as one of the risk factors that result from intense social media use. Previous studies have associated mental health with academic success (Chau et al. 2016; Lyons & Huebne, 2016; Ryan & Deci, 2017; Simovska et al., 2016), giving this research context much attention as it relates to students (WHO, 2014). Although moderate use of social media does not interfere with overall functioning and mental health (Twigg et al., 2020), adverse effects originating from intense social media engagement have been examined in the context of excessive and problematic usage.

Problematic social media use is intense social networking use that limits other social activities, studies, interpersonal relationships, and mental health (Raudsepp, 2019). It is important to distinguish between intense social networking use and problematic use. Problematic social media use is characterized by overuse of social media, driven by a motivation to use social media, and devoting too much time and effort to social media activities (Andreassen, 2015). Intense social networking use is the frequent use of multiple types of online social media activities through multiple platforms. Intense social media users may regulate their intense social networking use, whereas problematic users may not. Research investigating the adverse effects of problematic usage has indicated that it may lead to deteriorated mental health (Lin et al.,

2016) and overall physical health (Brailovskaia et al., 2019; Pontes, 2017). Deteriorating mental health can further influence a range of psychiatric outcomes and behaviors, including, but not limited to, increased severity of insomnia, stress, depression, and anxiety (Brailovskaia & Margraf, 2017; Brailovskaia et al., 2019). Psychologists indicate that anxiety, stress, insomnia, and depression are significant obstacles for teens and young adults. U.S. teens lose about 90 minutes of sleep each school night from grade 6 (about 11-12 years old) to grade 12 (about 17-18 years old (Tarokh et al., 2016). A more recent report from the Centers for Disease Control, using the Youth Behavior Risk Surveillance Data from 2007, 2009, 2011, and 2014 (50,370 U.S. students), found that two-thirds of students in grades 9 to 12 reported seven hours or fewer if sleep on school nights.

According to Akram and Kumar (2017), the problematic use of social media adversely affects students' physical and mental health by reducing physical activity and impeding motivation to connect physically with the general population. Intense social media use can attribute to poor body image and low self-esteem (Elsherif and Abdelraof's, 2018), due to the fact that adolescence is a period of increased self-esteem vulnerability and likelihood of depression and anxiety (McLaughlin & King, 2015). For example, students who are used to receiving social support on social media when they post pictures or statuses may unexpectedly receive a negative comment or negative feedback. This can change the student's mood, and/or their body image, which ultimately affects self-esteem and engagement. This kind of consistent behavior can affect how he or she participates in school and can affect his or her ability to learn.

Although social media use may positively influence user confidence with greater social support (Tifferet, 2019; Tobi et al., 2013), researchers also report that it can increase an individual's exposure to negative social interactions (cyberbullying), which may negatively impact mood and mental health (Seabrook et al., 2016). Scholars have also found that social media use can lead to depression (Błachnio et al., 2015) and cause a decrease in self-esteem (Jan et al., 2017). Individuals with low self-esteem are more prone to internet addiction (Chen et al., 2020). Banjanin et al. (2015) reported that students who spend more time online and engaged in social media tend to experience significant levels of anxiety and depression, whether it is due to the lack of quality in their interpersonal connections or the assumption that their SM “friends” are happier and more successful. The literature suggested a relationship between intense social networking use and mental health (anxiety, depression, and low self-esteem), a negative correlation with academic performance is implicated.

Effects of Social Media on Sleep Disturbance

People with low self-efficacy tend to gain a sense of accomplishment by investing in the Internet (Chen et al., 2020), which causes problematic use. Due to the prevalence of social media use among adolescents, researchers have found it valuable to investigate the link between their problematic social media use, sleep practices, and associated experiences at school. Specifically, problematic social networking is associated with poor school experiences, which result from poor sleep habits (Vernon et al., 2015). Vernon et al.'s (2015) findings suggest that adolescents are vulnerable to adverse consequences from social networking, including sleep disturbances, sleep quality, and school satisfaction. Levenson et al. (2017) assessed a nationally representative sample of 1,788 U.S. young adults and found participants with higher social media use had significantly greater probabilities of having sleep disturbance. For example, compared to those in the lowest quartile of social media use per day, those in the highest quartile had an AOR of 1.95 (95% CI = 1.37-2.79) for sleep disturbance.

Sleep disturbance includes all or some of the following factors: lower sleep efficiency, more sleep interruptions, less total sleep time, inferior sleep quality, and more daytime tiredness (Van den Eijnden et al., 2021). It has been estimated that 25 to 40% of children and adolescents suffer from sleep disturbances (insufficient sleep disturbance) (Thumann et al., 2019). Sleep disturbance and insufficient sleep duration are associated with daytime sleepiness and a range of poor health outcomes. According to Woods and Scott (2016), sleep interruptions originating from alerts and anxiety due to fear of missing new content are just two of the many possible connections between social media use and inadequate sleep in young children and adolescents.

Raudsepp (2019) revealed that increased social media use predicted sleep disturbances and depressive symptoms with changes in daily performance among adolescents. Moreover, the longitudinal findings of Van den Eijnden et al. (2021) implied that more intense and more problematic social media use was associated with later bedtime and lower sleep quality. Insufficient sleep negatively affects cognitive performance, mood, immune function, cardiovascular risk, weight, and metabolism (Levenson et al., 2016). In addition, Costa and Pereira (2019) reported that total sleep deprivation produces harmful effects on brain function, especially the functions associated with the frontal lobe (involved in alertness, attention, decision-making, and cognitive processes) and the thalamus. This indicates that lack of sleep impairs students' ability to focus and learn efficiently. Though not all sleep deprivation can be attributed to intense social networking use, there is a direct link between decreased attention and working memory due to sleep deprivation (Valdez et al., 2020), which ultimately results in decreased student engagement. Although, there is still a need for research to support the relationship between intense social networking use, sleep quality, and quantity. The literature suggests a correlation between intense social networking use and sleep disturbance among young adolescents (Buda et al., 2020; Duradoni et al., 2020; Sha et al., 2019).

Social Media, Motivation, and Effort Regulation

Motivation is important for academic success and can be affected by social media engagement (Barton et al., 2018). In this context, motivation involves students' abilities to establish goals for academic tasks and their effort to complete the task even when it does not interest them (Zusho, 2017). Intense social networking use is connected to sleep disturbances. This leads to decreased concentration, motivation, fatigue, and delayed physical movements and responses (National Institute of Mental Health, 2016). Intense social networking use can also affect mental health (Lin et al., 2016), influencing motivation. Consequently, social media users' insufficient academic performance can be attributed to decreased motivation. Research shows that social media can distract students from their studies (Balakrishnan et al., 2016). Therefore, motivation or effort regulation is fundamental in increasing effort and initiation for continuance in productive activities like schoolwork (Nguyen & Ikeda, 2015).

The literature suggests that social media influences students' ability and motivation to control their effort in completing tasks which may, in turn, affect their overall academic performance (Barton et al., 2018). In other words, effort regulation can predict academic achievement. Therefore, the literature will examine this psychosocial factor only related to sleep disturbance, mental health, and the social cognitive theory (SCT). Effort regulation is characterized by an individual's ability to persist during complex tasks, exerting the effort necessary to complete the task while restraining engagement in a more favorable task (Richardson et al., 2012). Choosing a more favorable task, such as social media engagement, may require students not to persist in the primary, study-related task when it becomes challenging or for which they lack motivation (Barton et al., 2018). In this instance, self-efficacy can mitigate the negative effects of intense social networking use on sleep disturbance, mental health, and how these influence motivation. Increased self-efficacy accounted for mood changes and perceived stress that explain, in part, improved sleep quality (Caldwell et al., 2010). Selfefficacy is a key personal influence in Bandura's (1997) model of reciprocal interactions that can affect motivational outcomes.

The SCT theory states that being behaviorally and motivationally active in the learning process contributes to students' academic performance (Kirschner & Karpinski, 2010). Therefore, teachers and parents need to establish the proper goals to influence motivational outcomes in children. Although performance goals can influence motivational outcomes, research studies support that learning goals lead to better motivational outcomes and achievement, particularly over more extended periods (Schunk & DiBenedetto, 2020). Furthermore, feedback from teachers and peers and persuasive verbal statements can decrease anxiety, enhancing motivational outcomes. Research supports the idea that self-efficacy influences one's choice of activities, effort, persistence, achievement, and self-regulation, and, in turn, is affected by the results of one's achievement efforts (Bandura, 1997, Honicke & Broadbent, 2016; Schunk & Usher, 2019). This study aims to employ effort regulation and self-efficacy to consider how young adolescents manage their motivation to elicit positive outcomes when academically challenged and the potential mental health effects possibly catalyzed by intense social networking use.

Summary

Social media use—and its overuse—is a topic of interest to all educational stakeholders, especially in K-12. The literature implies that intense social networking use can become problematic when the individual develops an addiction to the point where it significantly affects social activities, studies, interpersonal relationships, and mental health. Given the reality of a still-developing teenage brain, this intense social networking use can influence psychosocial factors like effort regulation/motivation (Barton et al., 2018), mental health (Chau et al. 2016), and sleep disturbance (Sha et al., 2019)—all essential as influencers of academic achievement and adaptive behavioral functioning. Moderate use (anything less than 3 hours per day) of social media does not seem to interfere with overall daily functioning and mental health (Twigg et al., 2020). Moreover, positive outcomes have been reported related to purposeful academic and social media engagement as a learning tool (Irwin et al., 2012; Junco, 2012; Karvounidis et al., 2014; Mbatha, 2014; Sobaih et al., 2016).

Nevertheless, students, educators, and parents should still be cognizant of the mixed results and the potential adverse effects of intense social networking use. It can negatively influence academic outcomes, such as test scores, grade point average (GPA), homework completion, studying time, and time spent reading (Balakrishnan et al., 2016; Walsh et al., 2013). Many studies suggest that students overuse social networking apps and that this simply occurs at the expense of time dedicated to focusing on academics (Alwagait et al., 2015). However, it is not only the time students expend on social media that influences their academic performance, but also the nature of social media activities across platforms that differentiate between high and lower school achievers.

This literature review explored how intense social networking use can influence psychosocial factors—motivation, mental health, and sleep disturbance—and examined their associations with academic self-efficacy and poor academic performance. Educational stakeholders can infer that intense social networking use may lead to poor motivation, mental health, and sleep, which directly influences the cognitive processes involved in academic performance. Another conspicuous implication is that expected outcomes were the most influential predictor of intense social networking use (Lin & Chang, 2018). In addition, general beliefs related to self-efficacy are directly associated with most of the expected outcomes of social media usage. In Lin & Chang's (2018) study, the researchers utilized a general self-efficacy measurement scale. The relationship found between self-efficacy and expected outcomes was consistent with the results of existing studies. However, this study does not investigate the causation between expected outcomes and social media usage. The literature only supports the claim that there is a relationship; there is no indication that forethought is involved in social media use.

A gap in the literature exists concerning cause-and-effect relationships not being identified. Many of the studies were conducted outside of the U.S., with most participants being young college students. There has been no focus on how the intensity of social media engagement affects at-risk students with low socioeconomic status. Using Bandura's (1986) 1997) durable self-efficacy theory as a framework through which to view this thorny phenomenon of social media use, this study will extend the existing research on social media use by examining a specific demographic, thus possibly enabling administrators to educate young adolescents better on the pitfalls of excessive or problematic social media use. It will also provide a means of implementing best practices for the effective use of social media as a learning tool in the middle school classroom curriculum by using outcome expectancies and self-efficacy as a basis for teacher intervention. Social cognitive theory suggests a framework that can be used to develop teachers professionally to elicit the proper goals to influence motivational outcomes in young adolescents. The hope is that research in this area will continue to expand beyond middle school at-risk students to look closer at different demographic variables, and the relationship between intense social networking use and high school students, and even elementary students.

CHAPTER THREE: METHODS

Overview

The purpose of this quantitative, predictive, non-experimental correlational study was to describe and justify a design that will address the research questions. This chapter begins by introducing the design of the study, including full definitions of all variables. The research questions and hypothesis are then discussed. The participants and setting and a full description of the study's sampling and data collection procedures will be provided. Instrumentation, procedures, and data analysis plans follow.

Design

The researcher used a quantitative, non-experimental correlational design to determine if there was a relationship between middle school at-risk students' categorical test scores as measured by the school district's science and math benchmark assessments and the predictor variables, intensity of social networking use, SES, and gender. Examining the predictive relationship between a set of independent variables and a dependent variable is one of the primary purposes of quantitative correlational design (Gall, 2007). This type of predictive analysis utilizes previous data to predict future outcomes and is one of the most commonly used in correlational studies (Gall, 2007; Warner, 2013). The quantitative correlational approach was a good choice for this study because it allowed the researcher to identify the degree and direction (i.e., positive or negative) of the relationship between two or more variables and explore possible predictive relationships (Gall et al., 2007). In addition, a nonexperimental correlational design allowed the researcher to focus on the magnitude and nature of the relationship between variables that are measured, but not manipulated in the study (Creswell & Guetterman, 2019). Although predictive, correlational research does not allow one to determine underlying causes within data, relationship-based research is essential in the social sciences because it can illuminate patterns and relationships in data to inform decision-making (Astin, 1993; Field, 2018). Moreover, if a researcher seeks to understand possible predictive relationships between existing variables, correlational research is the most accurate to use (Gall et al., 2007; Warner, 2013).

The purpose of the current study was to determine if the predictor variables (intense social networking use, SES, and gender) were sufficient to predict categorical test scores in math and science for middle school at-risk students. The predictor variable, intense online social networking use, is defined as frequency and time spent on multiple types of online social media activities through multiple types of platforms (Li et al., 2016). The additional predictor variables were SES and gender. Gender has an operational definition of male or female based on physiological/bodily aspects (*sex*)—what the American Psychological Association refers to as "sex role" (APA, 2015). SES in this context is defined as a measure of the parent's education level, occupation, and income (He et al., 2020) and is represented in this study by students who qualify for free or reduced lunch. The criterion variable, two benchmark assessments, is defined as formative assessments administered periodically throughout the school year, at specified times during a curriculum sequence, to evaluate students' knowledge and skills relative to an explicit set of longer-term learning goals (Herman et al., 2010).

Research Questions

RQ1: How accurately can at-risk middle school students' ranked-ordered *math* test scores be predicted from a linear combination of intense online social networking use, socioeconomic status (SES), and gender?

RQ2: How accurately can at-risk middle school students' rank-ordered *science* test scores be predicted from a linear combination of intense online social networking use, socioeconomic status (SES), and gender?

Hypotheses

The null hypotheses for this study are:

$H_0$1: There is no significant predictive relationship between the rank-ordered criterion variable math test scores, as measured by the grade-level benchmark assessment, and the linear combination of predictor variables (socioeconomic status (SES), gender, and intense social networking use as measured by the SNAIS survey) for middle school at-risk students.

$H_0$2: There is no significant predictive relationship between the rank-ordered criterion variable science test scores, as measured by the grade-level benchmark assessment, and the linear combination of predictor variables (socioeconomic status (SES), gender, and intense social networking use, as measured by the SNAIS survey) for middle school at-risk students.

Participants and Setting

Population

Based on school analytics for the current school year (2021-2022), the population size for the middle school in this study was 769 students. A convenience sample of 150 (8^{th}) grade middle school at-risk students between the ages of 13 and 14 was drawn from this population. For the purposes of this study, at-risk refers to those students whose poor academic grades puts them at-risk of academic failure. Public demographic data of the school district showed an ethnic distribution of 76.5% Black, 22.5% Hispanic, and 1% other race, representative of the current three years within this middle school. The male-to-female ratio of enrolled students is 49.5% and 50.5%, respectively. Students from economically disadvantaged homes make up 89.5% of the student body and are defined as those who qualify for free or reduced lunch. Although demographic information, such as gender and socioeconomic status will be collected, eligibility to participate was not contingent upon these factors.

Participants

The researcher selected a convenience sample from the school in which they are employed, though not from students for whom they have direct responsibility. This sample was large enough to meet the sample-size requirements of ordinal logistic regression analysis (Gall et al., 2007). For this study, the number of participants in the convenience sample was 150 middle school eighth-grade students between the ages 13 and 14. According to Gall et al. (2007), this exceeded the required minimum sample size requirement of $N = 30$ for correlational research, which is at least 10 observations per variable. Research that asks adolescents to participate in surveys is usually a voluntary recruitment strategy with high non-response, as opposed to compulsory participation for school purposes. The 150 sample size was reduce to 68 participants due to non-response even though there was compensation. The final sample included 32 male students and 36 female students, with no students who identified as White or Caucasian, 52 identified as African-American or Black, 13 as Hispanic or Latino, two as Other, and one who did not report.

Setting

Data was collected through an online survey during the spring semester of the 2021-2022 school year. An initial survey was provided for the potential participants to determine their eligibility and willingness to participate in the study. The participants were required to be active on at least one social media platform and utilize a smartphone to be included. They were selected with no consideration of gender or current grade in the researcher's class. The initial survey contained demographic information, which required self-reporting the participant's age, gender, race, and whether or not they qualified for free or reduced lunch. Participants accessed the surveys via a hyperlink provided through Google classroom. They were advised of the time frame for the study, which was one week. The estimated time to complete the survey was about three minutes. Participants were also advised that participation was voluntary. They were excluded from the study if they did not use social media and were not using smartphones. They were also excluded if they decided for any reason that they did not want to continue. Due to the online nature of the survey, participants were able to complete the survey at their earliest convenience.

Instrumentation

The participants for this study came from a convenience sample of middle school students located in Northeast New Jersey in the United States during the 2021-2022 school year. They were recruited from an 8th grade science classroom . All students with permission to participate were included in the study. The school district selected was a middle-to-low income Title I urban district. An elementary or secondary school is considered to be Part A (Title I) school when they receive federal funds due to high percentages of children from low-income families that need help to ensure that all children meet challenging state academic standards ("Title I, Part A Program," 2018). The Title I school district, used for this study faced social and economic inequities, including a high number of at-risk students. These students are referred to as "at-risk" because they tend to have low socioeconomic status (SES), live in a disadvantaged urban neighborhood, display lack of interest in school, often have low standardized test scores, represent non-native English speakers and minority groups, and have poor overall school results that puts them at-risk of academic failure (Smith, 2011).

Benchmark Assessment

Benchmark assessments are formative assessments administered periodically throughout the school year, at specified times during a curriculum sequence, to evaluate students' knowledge and skills relative to an explicit set of longer-term learning goals (Herman et al., 2010). This study looked at two criterion variables, math and science test scores. The purpose of the benchmark instrument was to measure each student's performance on the 8th grade Common Core Math Standards based on Cycle 1, and the Next Generation Science Standards based on the Force and Motion Unit. Within K-12 education, the topics on which benchmarks should focus have been articulated in content standards (Marzano, 2017). Benchmark Assessments were used as a measure in numerous studies (Herman et al., 2010; Marzano, 2017; Mooney & Lastrapes, 2018; Paleologou et al., 2006; Snow et al., 2018). According to Sullivan (2011), when it comes to outcome measures such as surveys or a test, validity refers to the accuracy of measurement. Validity evidence based on test content is necessary for building a validity argument to support the use of a test for a particular purpose (Sireci & Faulkner-Bond, 2015). Evidence can be found in *content, response process, relationships to other variables,* and *consequences* (Sullivan, 2011).

Validity

The author argues that the Math and Science Benchmark Assessment is valid based on the following evidence. *Content* includes a description of the steps used to develop the instrument, which was provided by the district in professional development. Additionally, the items on the tests accurately and comprehensively represent the standards to be measured. They were used to interpret students' proficiency level and the specific knowledge or skill that needs to be taught, giving the instrument good construct and content validity. *Response process* for this school district includes training for the Edconnect platform used for testing, and also training on instructions for the test-takers, instructions for scoring, and clarity of the materials/standards. *Relationship to other variables* includes correlation of the scores on the math and science benchmark assessments to the scores on the high stakes New Jersey Student Learning Assessment (NJSLA) state tests, giving the tests criterion-related validity or predictive validity. The Department of Education also believes that the data on benchmarks can be used to interpret how well students will perform on end-of-year tests. Benchmark exams produce reliable and valid data to aid in predicting student success on high-stakes assessments (Marzano, 2017). *Consequences* for this benchmark are evidenced in diagnostic data provided by Edconnect, students who pass/fail, tend to perform the same in other content areas.

Reliability

Test publishers typically provide reliability indices for their benchmark assessments with other technical information about item difficulty and discrimination (Herman et al., 2010). However, this instrument is not a commercial benchmark test and was developed by the school district; so, there is no published reliability statistics. However, reliability is acceptable. Three statistical guidelines (Herman et al., 2010) are used by the district to evaluate the high reliability of the test items: (a) Fair and Unbiased—all students have access and it does not advantage some students over others (b) High Utility—the benchmark accomplished its intended purpose, to measure proficiency on specific Next Generation Standards in the same format as the New Jersey Student Learning Assessments, the state test (c) Balance—the benchmark is well aligned with district learning goals and state standards, provides good diagnosis information, and also accommodations for specific populations. Cronbach’s alpha was used to report reliability on the collected data.

Scale, Questions, and Measurement

The math benchmark consisted of 15-items with a total 20-point value, scored as a percentage out of 100. The science benchmark consisted of 23-items with a total 30-point value, scored as a percentage out of 100. The math and science benchmark instrument used a scale of five score groups to report student performance levels, it provides the following cut scores: exceed standards = 100, meets standards = 80, basic standards = 70, below basic standards = 50, far below basic standards = 30. The total scores are a summation of all the numerical values. For the benchmark scale, a score of 0 points is the lowest possible score and a score of 100 points is the highest possible score. Higher scores indicate higher proficiency levels, and lower scores indicate a serious lack of performance (students demonstrate little or no understanding of the knowledge and skills measured by the standards). The benchmark was administered by classroom teachers. Approximate time to complete instrument was 80 minutes, except for students that required the modification of extended time. Scoring data was obtained from Edconnect, which is the school district record system and testing platform.

The Social Networking Activity Intensity Scale (SNAIS)

This SNAIS was developed in China by Li et al. (2016). The purpose of this instrument was to measure the predictor variable, intense online social networking use. The SNAIS scale, found in Appendix E, is a questionnaire that gathered data using self-reported survey questions (Gall et al., 2007). According to the developers, this is the first tool that assesses online social network use intensity (SNUI) among middle school students based on diverse social networking activities, and it should facilitate more research in the future (Li et al., 2016). The instrument was used in numerous studies (Li et al., 2016; Redmond, 2019; Sigerson & Cheng, 2018). To develop the instrument, the authors generated a list of items after conducting a literature review regarding online activities and related measures for social networking use. Then, a panel consisting of a behavioral scientist, two psychologists, and an epidemiologist refined the list and eliminated the overlapping items while combining others with similar meanings. Finally, they extracted 14-items from a 38-item pool. The 14-item scale was pilot tested among 77 middle school students who were social network users (Li et al., 2016).

Validity

The SNAIS measures intense social networking use. Two constructs—social function and entertainment—were established. Social function related to the social interactions on social media (questions 1-10) and entertainment was based on the entertainment content on social media (questions 11-14). According to Li et al. (2016), these two constructs, which emerged as the two subscales, Social Function Use Intensity (SFUI) and Entertainment Function Use Intensity (EFUI), have strong practical implications and can be used to understand various consequences of intense social networking use. The authors used both exploratory and confirmatory factor analyses (EFA and CFA) to investigate the construct validity of the instrument. EFA analysis extracted the factor structure of the first subsample, and for the second subsample, CFA was conducted. The results of the CFA confirmed the two-factor solution, showing acceptable goodness of fit to the data. They adopted Hu and Bentler's (1999) criteria for fit indices: RMSEA $< .08$ CFI $> .96$ TLI $> .96$.

Reliability

Overall, the reliability of the SNAIS is sufficient; the internal consistency of the whole scale was acceptable (Cronbach's $\alpha = .89$). The test-retest intra-class correlation coefficient was .85. However, its criterion, discriminant, and incremental validity have not been established, and there are minor concerns about the reliability of one of its subscales (the EFUI scale had an internal consistency below the standard cutoff of .70 (Cronbach's $\alpha = .60$). Li et al. (2016) believed that the EFUI subscale is still useful, considering its acceptable psychometric properties, and suggested that both subscales could be used together as social media engagement and entertainment are not mutually exclusive. Moreover, the SNAIS received multiple tests in two samples showing that it is stable over time, and there were no noticeable ceiling or floor effects. Sigerson & Cheng (2018) extracted the relevant psychometric information from the reviewed reports of Li et al. (2016) in the Results section and summarized the information in Table 1. All documents related to the instrument are included in Appendix E.

Table 1

Descriptions of Psychometric Characteristics and Assessments of the SNAIS Scale

Scale	Author	Year	Sample Size (n)	Internal consistency (α)	Test-retest Reliability (r)	Type of validity	Scale	Author
SNAIS (Sample1)	Li et al.	2016	455	.89	.85	Convergent validity. In a combined sample ($n = 910$), the whole scale as well as both factors had significant positive correlations with the FBI scale, social networking addiction, and Internet addiction.	SNAIS (Sample1)	Li et al.

Note. Reliability-based on an average of subscales rather than full scale. The numbers from this subsample are unavailable, so numbers from the combined sample are reported instead.

Scale, Questions, and Measurement

The SNAIS consists of a 14-item questionnaire with two subscales: the SFUI (Questions 1-10) measures social functions related to the social interactions on social media, and EFUI (Questions 11-14) measures entertainment content on social media. As stated before, the Social Function Use Intensity (SFUI) and Entertainment Function Use Intensity (EFUI) scales, have strong practical implications and can be used to understand various consequences of intense social networking use. The 14-items are written in the following question form: "How often have you performed the following social networking activities in the last month." These items cover three facets of social media engagement: (a) self-presentation, (b) action and participation, and (c) usage and activity counts (Sigerson & Cheng, 2018). The instrument uses a 5-point Likert scale from 0=Never, 1=Few, 2=Sometimes, 3=Often, 4=Always (Redmond, 2019). The total score on the SNAIS is the summation of all the numerical values on both subscales. For the SFUI scale, a score of 0 points is the lowest possible score and a score of 40 points is the highest possible score. For the EFUI scale, a score of 0 is the lowest possible score and a score of 16 is the highest possible score. Higher scores indicate higher usage levels; however, there is no specific cut score for low, moderate, or high social network activity usage (Redmond, 2019). The approximate time to complete instrument (Li et al., 2016) is 3 to 5 minutes. See Appendix E for the full SNAIS scale, permission to use, and instruction on administering the instrument.

Demographic Questionnaire

Demographic information for respondents was collected via a brief demographic questionnaire, which was part of the online survey. The demographic questionnaire (see Appendix C) was used to collect information on respondents' gender, age, and socioeconomic status. All questions were mandatory and required a response; participants could not submit the

SNAIS survey or demographic questionnaire without completing every aspect. The demographic questionnaire was adapted from the questionnaire used in the study by Li et al. (2016).

Procedures

Upon obtaining approval from the Institutional Review Board (IRB), the researcher forwarded an email to the building Principal and Superintendent of Schools to ask for permission to recruit students for the current research. See Appendix A. After the appropriate authorities granted school consent, the researcher generated a Google Classroom code to be an information hub. The researcher used the Google classroom to create and organize all related information for the study including the purpose of the study, survey link, and deadlines. Two teachers, math and science, was also recruited by the researcher to host the study. Participants were then conveniently selected from one of these 8th grade classrooms.

The researcher asked the subject teachers to post and announce the recruitment letter in their classrooms (see Appendix B) to elicit volunteers from the class (virtual and physical). Students were briefed of the inclusion criteria through the recruitment letter (see Appendix B). The inclusion criteria required participants to be in the eighth-grade (13-14 years old), be active on at least one social media platform and utilize smartphones. The teacher also gave interested students a recruitment letter to take home to their parents with a consent form attached. This was executed close to the beginning of the marking period or grading cycle (a completed marking period is measured by two and half months in this school district). They were given three days to return the consent forms. The subject teachers informed students that they would receive further instructions on how to complete the study when they returned their consent forms (Appendix C).

The consent form provided the contact information for the researcher and informed the parents of the voluntary nature of the study, procedures, and any benefits that the participants received (and included incentive in the form of $10 gift cards). They were also informed that their child might terminate their participation at any time. When students returned the consent forms with parental consent to participate in the study, they were enrolled in the researcher's Google classroom using a provided code. Any research data or documents with personal identifiers was stored on a password-protected computer or locked filing cabinet that was only available to the researcher.

When participants returned their signed consent forms, they were then given the google classroom code to ensure that only students with a returned consent form filled out the survey. The survey link from Survey Monkey was posted in the google classroom, and a two-week deadline was established. Students were expected to complete the online survey on a computer or cell phone within the two-week period at their own convenience. The survey required 3-5 minutes and was not required to be completed during instructional time. Before they began the survey, participants were asked to have math and science benchmark test scores on hand (students access their grades through PowerSchool portal). The study's survey was presented as a continuous, online single-page survey with three sections: (a) The demographic questions, (b) SNAIS survey questions (c), and the self-reported categorical test scores. Participants clicked 'submit' to submit their responses.

SurveyMonkey a secured website, ensured anonymity and privacy on the surveys. Furthermore, this website allowed the researcher to download survey results to spreadsheets and SPSS. Demographic questions such as age, gender, race, and whether or not they qualify for free or reduced lunch was presented in the survey on the same page. Each SNAIS question required a response, meaning participants could not move forward without answering all questions. However, demographic questions (inclusion criteria) had skip logic. Skip logic allowed the researcher to send respondents to a future point in the survey based on how they answer a question. For instance, if respondents indicated that they did not use any social media or if they responded that they did not have a smartphone, they would immediately be skipped to the end of the survey.

After the deadline to participate in the study, the survey was closed on SurveyMonkey. The researcher downloaded and saved the raw data from a secure computer into an Excel spreadsheet before entering the data in IBM SPSS statistics to begin statistical analysis, and deleting any identifiers such as IP addresses. The researcher also deleted incomplete surveys, participants that were skipped due to skip logic, or participants that did not record their gender or SES but completed the survey. This accounted for much of the reduction of the sample, even though students were informed of the inclusion criteria in the recruitment letter.

The researcher sorted participants' gender and coded for entry into SPSS: 1—male and 2 —female. No participant checked 'other'. SES was also coded and entered into SPSS: 1— Free-reduced lunch and 2 —no free/reduced lunch. Next, using the key for the SNAIS survey, the researcher sorted the individual responses to the 14 survey questions to determine the numeric level of "How often participants performed the following social networking activities in the last month": 0=Never, 1=Few, 2=Sometimes, 3=Often, 4=Always. According to Redmond (2019), higher scores indicate higher usage levels; however, there is no specific cut score for low, moderate, or high social network activity usage. In this study, a score of 0 points is the lowest possible score and a score of 56 points is the highest possible score.

Part of the data collecting included the researcher asking participants to self-report their math and science benchmark test scores on the survey (as per the IRB), to keep the survey anonymous. The researcher sorted participants' math and science test grades in six categorical score groups in SPSS: 1 for 0-50%, 2 for 51-60%, 3 for 61-70%, 4 for 71-80%, 5 for 81-90%, and 6 for 91-100%. A high score of 6 on the math or science test means that the student had complete understanding of the course material, whereas a low score of 1 means that the student has little to no understanding of the course material. For the benchmark scale, a score of 0 points is the lowest possible score and a score of 100 points is the highest possible score. Students accessed benchmark test scores on PowerSchool, a district software that provides parents/students in grades 6-12 with real-time access to classroom grades and attendance. Subsequently, all survey responses were anonymous, and access was limited to the researcher.

Data Analysis

In the current quantitative, non-experimental correlational study, an ordinal logistic regression procedure in SPSS was used to perform the analysis and test the hypothesis related to the predictors of students' test scores. This is an appropriate statistical method for the analysis of the current data, since the dependent variable is ordinal, and we are looking for the explanation of the relationship between math and science test scores and many covariates (factors). An ordinal variable is a categorical variable for which there is a clear ordering of the category levels (Warner, 2013). Ordinal logistic regression was appropriate for this study because the criterion variable (math and science test scores) is categorical. If the dependent variable is ordinal or categorical, logistic regression analysis should be used instead of linear regression (Warner, 2020). An ordinal logistic regression design also aligned with the research questions because this design allowed the researcher to determine if participants gender, SES, and intensity of social networking use was predictive of their math and science test scores. Intensity of social networking use was determined by the students' responses to the questions on the SNAIS survey.

The goal of this analysis was to predict the odds of students scoring in a higher category of the science and math test on the basis of one or more of the predictor variables.

According to Warner (2020), ordinal logistic regression does not require the same restrictive assumptions as multiple regression. For an ordinal logistic regression in which scores on a quantitative Y variable are predicted from scores on quantitative X variables, there are four assumptions: (a) the dependent variable should be measured at the ordinal level; (b) one or more independent variables are continuous, ordinal, or categorical (including dichotomous variables); (c) no multicollinearity among the independent or predictor variables; (d) there are proportional odds (Warner, 2020). The dependent variable meets the first assumption because the researcher categorized test scores as an ordinal variable in the following categories: 0-50, 51-60, 61-70, 71-80, 81-90, 91-100. The three independent variables of this study meet the second assumption because they include gender (categorical), SES (categorical), and intense social networking use. The third and fourth statistical assumption for ordinal logistic regression relate to how the data fits the ordinal regression model.

After identifying that the first two assumptions were met, a test calculating R^2 (the multiple correlation coefficient) was conducted to ensure the absence of multicollinearity between the predictor variables. The absence of multicollinearity assumed that predictor variables were not highly correlated and were assessed using the variance inflation factor (VIF). VIF values that are too high or greater than 10 suggest multicollinearity, violating this assumption. The acceptable values on this test were between 1 and 5, showing that each predictor variable was not highly correlated, which would mean they essentially provided the same information about the criterion variable. In the extreme case, if two predictors are perfectly correlated, it is impossible to distinguish their predictive contributions (Warner, 2020). A good second predictor correlates as little as possible with the first predictor, and so on.

Next, the test of parallel lines (assumption of proportional odds) was done to each independent variable to determine if the relationship between the independent variable and dependent variable was the same across all comparisons (Osborne, 2017). A less restrictive model, multinomial logit model was used. After the assumption was satisfied, a full likelihood ratio chi-squared test was used to compare the fit of the final model over the null model (Field, 2018). The Goodness- of-Fit test was done to determine whether the model revealed a good fit to the data.

Running logistic regression analysis also allowed the researcher to obtain both Wald tests of the predictors under Parameter Estimates and Likelihood ratio tests under the Model Fitting Information. For the most part, the *p*-values from both tables were very consistent. According to Warner (2020), when odds are less than 1, the target event is less likely to happen than the alternative outcome. When odds are greater than 1, the target event is more likely to happen than the alternative outcome. When the odds exactly equal 1, the target event has an equal chance of happening versus not happening. An odds ratio = 1 suggests no predicted change in the likelihood of being in a higher category of the dependent variable as values on an independent variable increase.

CHAPTER FOUR: FINDINGS

Overview

This chapter details the results of this quantitative, predictive, non-experimental correlational study to determine if a predictive relationship exists between math and science test scores, as measured by the benchmark assessment for middle school at-risk students and intensity of online social networking use, as measured by the SNAIS instrument—while considering the possible role of gender and socioeconomic status. The Findings section includes the research question, null hypothesis, data screening, descriptive statistics, assumption testing, and results. The study was designed using ordinal regression analysis to test the null hypotheses related to the predictors of students' test scores and to answer the following research questions:

Research Questions

RQ1: How accurately can at-risk middle school students' ranked-ordered *math* test scores be predicted from a linear combination of intense online social networking use, socioeconomic status (SES), and gender?

RQ2: How accurately can at-risk middle school students' rank-ordered *science* test scores be predicted from a linear combination of intense online social networking use, socioeconomic status (SES), and gender?

Null Hypotheses

The null hypotheses for this study are:

$H_0$1: There is no significant predictive relationship between the rank-ordered criterion variable math test scores, as measured by the grade-level benchmark assessment, and the linear combination of predictor variables (socioeconomic status (SES), gender, and intense social networking use as measured by the SNAIS survey) for middle school at-risk students.

$H_0$2: There is no significant predictive relationship between the rank-ordered criterion variable science test scores, as measured by the grade-level benchmark assessment, and the linear combination of predictor variables (socioeconomic status (SES), gender, and intense social networking use, as measured by the SNAIS survey) for middle school at-risk students.

Descriptive Statistics

The sample consisted of 68 participants. Scores on the math and science tests ranged from 0 to 100%; coded into six categorical score groups: 1 for 0-50%, 2 for 51-60%, 3 for 61-70%, 4 for 71-80%, 5 for 81-90%, and 6 for 91-100%. A high score of 6 on the math or science test and means that the student had complete understanding of the course material, whereas a low score of 1 means that the student has little to no understanding of the course material. Intense social media use was measured using the Scores on the Social Networking Activity Intensity Scale (SNAIS). Individual responses to the 14 questions on the SNAIS survey was coded using a 5 point Likert scale: 0=Never, 1=Few, 2=Sometimes, 3=Often, 4=Always. A high score of 56 means the student had high level of usage, however, there is no specific cut score for low, moderate, or high social network activity usage (Redmond, 2019). For sake of this study, the researcher determined a score of 12 indicates little to no social media usage by using the lowest scores on the Likert scale that does not include 0. Descriptive statistics can be found in Table 2.

Table 2

Descriptive Statistics

	N	Minimum	Maximum	*M*	*SD*
Gender	68	1.00	2.00	1.5294	.50285
SES	68	1.00	2.00	1.0294	.17021
SNAIS	68	12.00	56.00	36.4265	10.80950
Math	68	1.00	6.00	3.7794	1.29114
Science	68	1.00	6.00	3.6912	1.51861

Valid N (listwise)	68

Results

Data Screening

To create an electronic data set, data was imported from SurveyMonkey into the Statistical Package of the Social Sciences (SPSS). Before testing the assumptions, the researcher sorted the data and all categorical variables were coded for use in SPSS. The data was inspected visually for inconsistencies on each variable by proofreading survey questions completed by participants. No data errors or inconsistencies were identified. Of the original 150 potential participants, 68 completed the initial survey on SurveyMonkey and were included in the SPSS analysis. Incomplete surveys and surveys with inconsistent screening questions were removed from analysis, resulting in cases being reduced from 150 to 68.

Assumptions Testing

Assumption of Dependent Variable

The ordinal logistic regression requires that the predictor variable or dependent variable is measured at the ordinal level. The assumption was met. Table 3-4 represents the categorical and continuous variables for the study. The criterion variable, science test scores, depends on the same predictor variables, and so it is not presented.

Table 3

Categorical Variable Information

			N	Percent
Dependent Variable	Math	0-50%	4	5.9%
		50-60%	6	8.8%
		60-70%	17	25.0%
		70-80%	21	30.9%
		80-90%	14	20.6%
		90-100%	6	8.8%
		Total	68	100.0%
Factor	SES	free/reduced lunch	66	97.1%
		no free/reduced lunch	2	2.9%
		Total	68	100.0%
	Gender	Male	32	47.1%
		Female	36	52.9%
		Total	68	100.0%

Assumption of Independent Variable

The ordinal logistic regression requires that one or more independent variables are continuous, ordinal, or categorical (including dichotomous variables). This assumption was met.

Table 4

Continuous Variable Information

		N	Minimum	Maximum	*M*	*SD*
Covariate	SNAIS	68	12.00	56.00	36.4265	10.80950

Assumption of Multicollinearity

A Variance Inflation Factor (VIF) test was conducted to ensure the absence of multicollinearity. This test was run because if a predictor variable (x) is highly correlated with another predictor variable (x), they essentially provide the same information about the criterion variable. If the Variance Inflation Factor (VIF) is too high (greater than 10), then multicollinearity is present. The absence of multicollinearity was met as seen through the requirement of acceptable values between 1 and 5. See Table 5-6 for collinearity statistics.

Table 5

Collinearity Statistics

		Collinearity Statistics	
Model		Tolerance	VIF
1	Gender	.998	1.002
	SES	.998	1.002
	SNAIS	.996	1.004

a. Dependent Variable: Math

Table 6

Collinearity Statistics

		Collinearity Statistics	
Model		Tolerance	VIF
1	Gender	.998	1.002
	SES	.998	1.002
	SNAIS	.996	1.004

a. Dependent Variable: Science

Null Hypothesis One Results

Proportional Odds

For hypothesis one, an ordinal regression was conducted to see if there was a predictive relationship between math benchmark test scores, gender, SES, and intense social networking use (as measured by the SNAIS survey) of middle school 8th grade students. The independent variables were gender, SES, and SNAIS scores. The dependent variable was math test scores. Testing for proportional odds ensured that each independent variable had an identical effect at each cumulative split of the ordinal dependent variable (Osborne, 2017). The test of parallel lines compared two models: the null hypothesis and the alternative hypothesis. The result of the test of parallel lines indicated non-significance with $p = .810 > .05$. This was an indicator that the assumption was met. Results are seen in Table 7.

Table 7

Test of Parallel Lines

Model	-2 Log Likelihood	Chi-Square	*df*	Sig.
Null Hypothesis	190.520			
General	182.845[b]	7.675[c]	12	.810

The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.
a. Link function: Logit.
b. The log-likelihood value cannot be further increased after maximum number of step-halving.

c. The Chi-Square statistic is computed based on the log-likelihood value of the last iteration of the general model. Validity of the test is uncertain.

Overall Model Fit

Using SPSS, two methods were used to assess the overall model fit. The Pearson and Deviance goodness-of-fit tests measured how well the observed data fits the model or how poor the model is. In this analysis, the Pearson chi-square test indicated that the model was a good fit to the observed data, X^2 (232) = 204.078, p =.907, and the deviance goodness-of-fit test also indicated that the model was a good fit to the observed data, X^2 (232) = 163.003, p =.362. Both tests had a p-value > .05. Non-significant test results are indicators that the model fits the data well (Field, 2018).

Table 8

Goodness-of-Fit

	Chi-Square	*df*	Sig.
Pearson	204.078	232	.907
Deviance	163.003	232	1.000

Link function: Logit.

Pseudo R^2 measures was developed to provide something similar to the “percentage of explained variance” information available from a true multiple R^2, but its maximum value is often less than 1.0 (Warner, 2020). There is no strong guidance in the literature on how these “pseudo” R^2 values should be used or interpreted (Pituch & Stevens, 2016). Cox and Snell, Nagelkerke, and McFadden (Smith et al., 2020) were tested to explain the variance of the model, or the predictive power of the model. The results were reported but not considered in the final model development. The strength of the association between math test scores and SES, gender, and intensity of social networking use (SNAIS) was determined to be extremely weak according to Cox and Snell’s R^2 (.011) and Nagelkerke’s R^2 (.011). This result provides evidence that 1.1% of the variance in the criterion variable is being affected by SES, gender, and SNAIS. The results of all three are found in Table 9.

Table 9

Pseudo R^2	
Cox and Snell	.011
Nagelkerke	.011
McFadden	.003

Link function: Logit.

The likelihood-ratio test, presented in the Model Fitting Information table, is a better method of assessing model fit. It looks at the change in model fit when comparing the full model to the intercept-only model. This tested whether or not there is a significant improvement in fit of the Final model relative to the Intercept only model. In this case, the final model is not statistically significant in predicting the dependent variable over and above the intercept-only model, X^2 (3) = .753, p = .861.

Table 10

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	*df*	Sig.
Intercept Only	91.273			
Final	190.520	.753	3	.861

Link function: Logit.

Parameter Estimates

The final data test was used to determine parameter estimates. Parameter estimates provided the researcher with information about the ability to predict the results of one-unit change of the predictor provided that all other predictors remained constant. Further, the odds ratios were examined to measure the multiplicative change in the odds of being in a higher category on the dependent variable for every one unit increase on the independent variable, holding the remaining independent variables constant. Gender and SES are binary variables, so the slope can be thought of as the difference in log odds between groups. As a result, category 2 of the Gender and SES variable, identified an odds ratio = 1, which suggests no predicted change in the likelihood of being in a higher category as values on an independent variable increase. The model was further analyzed for predictive significance using the Wald chi-squared test and the odds ratios produced from the analysis. All predictor variables showed no significant effect, and thus the researcher failed to reject the null hypothesis. The odds of males being in a higher category of the dependent variable (or scoring higher) was 1.408 (95% CI, .596 to 3.327) times that of females, no statistically significant effect, X^2 (1) = .608, p = .435; this indicates that the odds of males scoring higher on the math test tended to be higher than the odds of females scoring higher on the math test, but the nonsignificant Wald test indicates that this difference was too small to be judged statistically significant.

In addition, the odds of students who received free/reduced lunch (SES) being in a higher category of the dependent variable (or scoring higher) was .804 (95% CI, .075 to 8.641) times that of students who received no free/reduced lunch (SES), no statistically significant effect, X^2 (1) = .302, p = .857. Exp(B) for SNAIS (intensity of social networking use) was 1.008. This indicates that for every one unit increase on the SNAIS, there is a predicted increase of .008 in the log odds of a student being in a higher category of the math test scores. The results are represented in Table 11.

Table 11

Parameter Estimates

Parameter		*B*	*SE*	95% Wald Confidence Interval Lower	95% Wald Confidence Interval Upper	Hypothesis Test Wald Chi-Square	Hypothesis Test *df*	Hypothesis Test Sig.	Exp (*B*)	95% Wald Confidence Interval for Exp(*B*) Lower	95% Wald Confidence Interval for Exp(*B*) Upper
Threshold	[Math =1.00]	-2.553	1.5189	-5.530	.424	2.824	1	.093	.078	.004	1.529
	[Math =2.00]	-1.540	1.4637	-4.409	1.328	1.108	1	.293	.214	.012	3.775
	[Math =3.00]	-.197	1.4457	-3.030	2.637	.018	1	.892	.822	.048	13.970
	[Math =4.00]	1.114	1.4555	-1.738	3.967	.586	1	.444	3.047	.176	52.823
	[Math =5.00]	2.590	1.4990	-.348	5.528	2.986	1	.084	13.335	.706	251.751
[SES=1.00]		-.218	1.2113	-2.592	2.156	.032	1	.857	.804	.075	8.641
[SES=2.00]		0[a]	.	.	.	.	.	.	1	.	.
[Gender=1.00]		.342	.4388	-.518	1.202	.608	1	.435	1.408	.596	3.327
[Gender=2.00]		0[a]	.	.	.	.	.	.	1	.	.
SNAIS (Scale)		.0081[b]	.0197	-.031	.047	.162	1	.687	1.008	.970	1.048

Notes. Dependent Variable: Math
Model: (Threshold), SES, Gender, SNAIS
a. Set to zero because this parameter is redundant.
b. Fixed at the displayed value.

Null Hypothesis Two Results

Proportional Odds

For hypothesis two, an ordinal regression was conducted to see if there was a predictive relationship between science benchmark test scores, gender, SES, and intense social networking use (as measured by the SNAIS survey) of middle school 8th grade students. The independent variables were gender, SES, and SNAIS scores. The dependent variable was science test scores. Testing for proportional odds ensured that each independent variable had an identical effect at each cumulative split of the ordinal dependent variable (Osborne, 2017). The test of parallel lines compared two models: the null hypothesis and the alternative hypothesis. The result of the test of parallel lines indicate non-significance with $p = .337 > .05$. This was an indicator that the assumption was met. Results are seen in Table 12.

Table 12

Test of Parallel Lines

Model	-2 Log Likelihood	Chi-Square	*df*	Sig.
Null Hypothesis	203.407			
Final	203.407	3.376	3	.337

Notes. The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.
a. Link function: Logit.

Overall Model Fit

Using SPSS, two methods were used to assess the overall model fit. The Pearson and Deviance goodness-of-fit tests measured how well the observed data fits the model or how poor the model is. In this analysis, the Pearson chi-square test indicated that the model was a good fit to the observed data, X^2 (232) = 233.541, $p = .459$, and the Deviance goodness-of-fit test also indicated that the model was a good fit to the observed data, X^2 (232) = 178.662, $p = .996$. Both tests had a p-value > .05. Non-significant test results are indicators that the model fits the data well (Field, 2018).

Table 13

Goodness-of-Fit

	Chi-Square	*df*	Sig.
Pearson	233.541	232	.459
Deviance	178.662	232	.996

Link function: Logit.

Pseudo R^2 measures was developed to provide something similar to the "percentage of explained variance" information available from a true multiple R^2, but its maximum value is often less than 1.0 (Warner, 2020). There is no strong guidance in the literature on how these "pseudo" R^2 values should be used or interpreted (Pituch & Stevens, 2016). Cox and Snell, Nagelkerke, and McFadden (Smith et al., 2020) were tested to explain the variance of the model, or the predictive power of the model. The results were reported but not considered in the final model development. The strength of the association between science test scores and SES, gender, and intensity of social networking use (SNAIS) was determined to be extremely weak according to Cox and Snell's R^2 (.048) and Nagelkerke's R^2 (.050). This result provides evidence that .04% or .05% of the variance in the criterion variable is being affected by SES, gender, and SNAIS. The results of all three are found in Table 14.

Table 14

Pseudo R^2	
Cox and Snell	.048
Nagelkerke	.050
McFadden	.014

Link function: Logit.

A likelihood-ratio test was used to compare the fit of the model to the intercept-only model to provide an idea of the value added. This tested whether or not there is a significant improvement in fit of the Final model relative to the Intercept only model. In this case, there is no significant improvement in fit of the Final model over the null model X^2 (3) = 3.376, p = .337. The model did not improve.

Table 15

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	*df*	Sig.
Intercept Only	206.784			
Final	203.407	3.376	3	.337

Link function: Logit.

Parameter Estimates

As mentioned before, the parameter estimates provided the researcher with information about the ability to predict the results of one-unit change of the predictor if all other predictors remained constant. Further, the odds ratios were examined to measure the multiplicative change in the odds of being in a higher category on the dependent variable for every one-unit increase on the independent variable, holding the remaining independent variables constant. Category 2 of the Gender and SES variable, identified an odds ratio = 1, which suggests no predicted change in the likelihood of being in a higher category as values on an independent variable increase.

The model was further analyzed for predictive significance using the Wald chi-squared test and the odds ratios produced from the analysis. All predictor variables showed no significant effect, and thus the researcher failed to reject the null hypothesis, concluding that the regression coefficient for the predictor variables have not been found to be statistically different from zero in estimating science test scores. The odds of males being in a higher category of the dependent variable (or scoring higher) was 1.725 (95% CI, .732 to 4.064) times that of females, no statistically significant effect, X^2 (1) = 1.553, p = .213; this indicates that the odds of males scoring higher on the science test tended to be higher than the odds of females scoring higher on the science test, but the nonsignificant Wald test tells us that this difference was too small to be judged statistically significant.

In addition, the odds of students who received free/reduced lunch (SES) being in a higher category of the dependent variable (or scoring higher) was 4.959 (95% CI, .328 to 74.982) times that of students who received no free/reduced lunch (SES), no statistically significant effect, X^2 (1) = 1.335, p = .248. Exp(B) for SNAIS (intensity of social networking use) was 1.008. This indicates that for every one unit increase on the SNAIS, there is a predicted decrease of -.014 in the log odds of a student being in a higher category of the science test scores. We can conclude that increasing social media usage decreased the odds of scoring higher on the science test. The results are represented in Table 16.

Table 16

Parameter Estimates

Parameter		*B*	*SE*	95% Wald Confidence Interval Lower	Upper	Hypothesis Test Wald Chi-Square	*df*	Sig.	Exp(*B*)	95% Wald Confidence Interval for Exp(B) Lower	Upper
Threshold	[Science=1.00]	-.909	1.6151	-4.075	2.256	.317	1	.573	.403	.017	9.548
	[Science=2.00]	.282	1.6036	-2.861	3.425	.031	1	.860	1.326	.057	30.724
	[Science=3.00]	.911	1.5969	-2.219	4.041	.326	1	.568	2.487	.109	56.894
	[Science=4.00]	1.977	1.6054	-1.169	5.124	1.517	1	.218	7.224	.311	167.991
	[Science=5.00]	3.558	1.6441	.336	6.781	4.684	1	.030	35.098	1.399	880.524
[SES=1.00]		1.601	1.3857	-1.115	4.317	1.335	1	.248	4.959	.328	74.982
[SES=2.00]		0[a]	.	.	.	.	.	.	1	.	.
[Gender=1.00]		.545	.4374	-.312	1.402	1.553	1	.213	1.725	.732	4.064
[Gender=2.00]		0[a]	.	.	.	.	.	.	1	.	.
SNAIS		-.014	.0201	-.053	.026	.464	1	.496	.986	.948	1.026
(Scale)		1[b]									

Notes. Dependent Variable: Science

Model: (Threshold), SES, Gender, SNAIS

a. Set to zero because this parameter is redundant.

b. Fixed at the displayed value.

CHAPTER FIVE: CONCLUSIONS

Overview

Chapter Five will provide discussions surrounding the results and implications of the study. In this chapter, failure to reject the null hypothesis is discussed along with the major findings in relation to the research questions. Limitations of this study and recommendations for future research is also discussed.

Discussion

The purpose of this quantitative, predictive, non-experimental correlational study was to determine if a relationship exists between math and science test scores (as measured by the benchmark assessment) for middle school at-risk students and intensity of online social networking use as measured by the SNAIS instrument—while considering the possible role of gender and socioeconomic status. The SNAIS survey was used to test the hypotheses.

One issue to keep in mind in interpretation of results is the nature of the original research design. This study was not experimental. Intensity of online social networking use was assessed in a survey, and none of the predictor variables were experimentally manipulated. Therefore, there can be no causal interpretations on the basis of a logistic regression analysis.

Hypothesis One or Research Question One

The first research question in the study asked, “How accurately can middle school at-risk students’ math test scores be predicted from a linear combination of intense online social networking use, socioeconomic status (SES), and gender?” The findings failed to reject the null hypothesis in RQ1. An ordinal logistic regression analysis was conducted to determine whether or not a statistical relationship existed between the categorical dependent variable and the predictor variables. The significance value associated with the chi-square was more than the predetermined alpha level (.05), and so the overall predictor variables were judged to have no statistically significant effect (Warner, 2013). Because of the analysis, the researcher failed to reject the null hypothesis.

These results suggest that students' high social media usage did not contribute to middle school students' math test scores. In contrast, more studies support the alternative hypothesis that there is a significant relationship between social media usage and academic grades. Several studies revealed that students who use social media more than average had a poor academic achievement and low level of concentration in the classroom (Al-Yafi et al., 2018; Imani et al., 2018; Kim et al., 2017; Kumar et al., 2018; Upadhayay & Guragain, 2017). Researchers have found that conclusively, intense social networking use can become problematic for students by raising various physical (Levenson et al., 2017), psychological (Ryan & Deci, 2017), and social concerns (Barton et al., 2018) in their daily lives. Therefore, it can be concluded that the regression coefficient for the predictor variables have not been found to be statistically different from zero in estimating math test scores for one of many reasons: poor measurement reliability, restricted range, Type II error, a relation that is not linear, an improperly specified model, and so forth (Warner, 2020).

Hypothesis Two or Research Question Two

The second research question asked, "How accurately can middle school at-risk students' science test scores be predicted from a linear combination of intense online social networking use, socioeconomic status (SES), and gender?" The findings also found no significant relationship between the predictor variables and the criterion variables. The researcher also failed to reject the null hypothesis in RQ2. These results suggest that students' high social media usage did not contribute to middle school students' science test scores. However, as stated before previous research indicates that intense social networking usage can become problematic, placing students at academic risk due to media multi-tasking (May & Elder, 2018), poor study habits, and limited capacity for effort-regulation (Barton et al., 2018). Social media certainly influences daily life among modern students (Rajeev, 2015), and they are more likely to become addicted to social media (Simsek et al., 2019). Based on the results in this study, there was a discrepancy of variance between observation and prediction, which could be the result of a type II error. A type II error (false-negative) occurs if the investigator fails to reject a null hypothesis that is actually false in the population (Son et al., 2022). This assumption is discussed in detail below.

Summary

There are a few explanations for the findings in this study. First, the likelihood that a study will be able to detect an association between a predictor variable and an outcome variable depends, of course, on the actual magnitude of that association in the target population. Both small sample sizes and low effect sizes reduce the power in the study. No matter what kind of statistical analysis is performed, the outcome of the analysis will be largely determined by the number of participants that make up each category of the dependent variable (Warner, 2020). If a researcher is interested in the effect of the predictor variables on math test scores, and only 4 people make up the 0-50 score group out of 68 participants, that means that these scores are so rare that it occurs only 4 times per 68 people. Therefore, the researcher needs to obtain a much larger total N, or sample a much larger number of cases to obtain enough data. On the other hand, the number of people that make up these score groups might have been a result of recall bias by students. This will be further discussed.

Second, math and science test scores were obtained via self-report, which may not have accurately assessed participants actual scores. Reliability of self-reported test scores was found to differ across subject areas (e.g., math and science). Students may have a slight yet consistent tendency to over-report achievement levels across academic subjects (Sticca et al., 2017). This can be attributed to the low number of students in the 0-50 test score group and 51-60 test score group.

To assess reliability of self-report data the researcher compared reported scores to trends on the New Jersey Department of Education (NJDOE) website, where school report cards can be publicly accessed. Using Descriptive statistics, the researcher identified the frequency of scores in math with 5.9% of students reporting scores between 0-50%, 8.8% reporting scores between 51-60, and a total of 85.3% reporting ranges between 61-100. The same frequency was used to identify scores in science with 10.3% of students reporting scores between 0-50, 16.2% reporting scores between 51-60, and 73.5% reporting scores between 61-100. Overall, the absolute value of over reporting was high; the patterns in scores were found to differ between math and science based on the school report card available on the NJDOE website.

Due to the cancellation of statewide assessments in 2019-20 and 2020-21 due to the COVID-19 pandemic, the data for those years are unavailable on the NJDOE website. However, the existing data (2018-2019) currently supports the academic trends of Title I school districts. The NJDOE reported that 10.2% of the student population in this Title I middle school met the proficiency rate on the Math state assessment. The district did not meet the proficiency rate for federal accountability. Seventy nine percentage of the student population in this middle school district scored a level 1 (not proficient) on the science state assessment, with only 19% at a level 3 and 2% at a level 4 (level 3 or 4 are considered proficient). The district did not meet the proficiency rate for federal accountability. Given their widespread use, it is important to specifically examine the accuracy of self-reported test scores to ascertain the extent of potential errors in estimating achievement levels (Sticca et al., 2017).

Third, to establish the effects of intense social networking use, we need accurate and valid instruments to measure adolescents' time spent with these media (Verbeij et al., 2021). The data shows only moderate social networking activity on the SNAIS with a total average score of 37. The total score on the SNAIS is the summation of all the numerical values (Redmond, 2019). A score of 0 points is the lowest possible score and a score of 70 points is the highest possible score. Higher scores indicate higher usage levels; however, there is no specific cut score for low, moderate, or high social network activity usage (Redmond, 2019). Although, the most prominent methodology for studying social media use is self-report surveys (Mieczkowski et al., 2020), research shows that these measures do not accurately reflect usage logs (Behavioral and Social Sciences at Nature Portfolio, 2021). The SNAIS instrument required participants to provide estimates of their social networking usage (self-reports) as a proxy for measures of actual media use by asking 14 questions written in the following question form: "How often have you performed the following social networking activities in the last month." A more accurate way to quantify media use is to examine smart device logs via Apple Screen Time or other usage-logging apps. New trends, such as social media addiction, are concerning to society because individuals can access social media more frequently from portable devices, such as computer tablets or cellular phones, compared with the past (He et al., 2020).

The results of this study contradicted past research that intended to address the relationship between intense social networking usage and test scores. The literature suggests that social media influences students' ability and motivation to control their effort in completing tasks which may, in turn, affect their overall academic performance (Barton et al., 2018). Intense social networking use can negatively influence academic outcomes, such as test scores, grade point average (GPA), homework completion, studying time, and time spent reading (Balakrishnan et al., 2016).

Theoretical Framework

The theoretical framework that supported this study included Albert Bandura’s Social Cognitive Theory (SCT), which states that a person's behavior is partially shaped and controlled by the influences of social networks (i.e., social systems) and the person's cognition (i.e., expectations, beliefs) (Bandura, 1989). This framework presents a psychological perspective on human functioning that emphasizes the critical role played by the social environment on motivation, learning, and self-regulation (Schunk & Usher, 2019). SCT suggests that outcome expectancy and self-efficacy are two significant determinants of behavior. People are more likely to engage in behaviors they anticipate to have positive outcomes or rewards than those they perceive otherwise (Bandura, 1982). Social media engagement increases among young adolescents due to its trends, they get preoccupied with social identity and self-gratification, which often has a negative influence on their academics, leading to attention, memory, and motivation issues as stated by Bandura (1977).

SCT was also used to analyze how outcome expectancies can increase intense social networking use, resulting in higher addictive tendencies. The overuse of social networks (social media addiction) has positive and negative academic, social, and health consequences for students (Jha et al., 2016). Poor academic achievement is one of the most important negative consequences (Azizi et al., 2019). Several studies revealed that students who used social media more than average had a poor academic achievement and low level of concentration in the classroom (Al-Yafi et al., 2018; Imani et al., 2018; Kim et al., 2017; Kumar et al., 2018; Upadhayay & Guragain, 2017). When the results were analyzed, high levels of intensity or usage showed no relationship to test scores. This can be attributed to self-reported grades or recall bias (Marciano & Camerini, 2020).

Given the importance of self-efficacy for academic outcomes, a large body of research has focused on investigating differences in levels of self-reported self-efficacy for demographic groups defined by gender, age, grade, and levels of prior knowledge, even culture/countries (Nielsen et al., 2017). SCT uses academic self-efficacy to mediate the relationship between social media use and academic performance (Hassell & Sukalich, 2016). Social models provided by this social networking environment convey a significant amount of information about human values, styles of thinking, and behavior (Bandura, 2001). Based on the literature, self-efficacy and outcome expectations both are predictors of achievement due to their motivational outcomes, but self-efficacy is the stronger predictor.

Implications

This study suggested that no significant relationship exists between math and science test scores for middle school at-risk students and intensity of online social networking use as measured by the SNAIS instrument—while considering the possible role of gender and socioeconomic status. Therefore, students who used high levels of social media should see no significant difference in their math and science test scores. This might be a false negative because there is enough evidence that supports the alternative hypothesis that there is a significant relationship between intense social networking usage and test scores (He et al., 2020; Malak et al., 2017; Oyeboade, 2017; Raudsepp, 2019; Simsek et al., 2019; Tekkant & Topaloglu, 2015). This study intended to extend the body of research and fill the gap by addressing how the intensity of social media engagement affects at-risk students with low socioeconomic status by examining young adolescents (13-15 years old). Students are one of the most important users of digital information and social networks. Therefore, failure to reject the null is inconsistent with the findings of other studies.

One of the key issues plaguing the existing studies on the use of the social networking sites (SNSs) is the lack of a uniform index for measuring the time spent on the sites (Olufadi, 2016). This study falls into the category of measuring intensity, not time spent on different social networking sites. The SNAIS instrument did not have a defined usage log of measuring time spent on SNSs. This research indicates that future researchers may need to reconsider much of the extant evidence regarding the log measures of intense social networking use that does not also apply device logs (Jones-Jang et al., 2020; Jürgens et al., 2019). Current smartphones provide the capabilities to display the percentage of time spent utilizing social media applications, which will allow more accurate tracking of social media usage (Hunt et al., 2018). As mentioned before, this is a more accurate way to quantify media use via Apple Screen Time or other usage-logging apps.

Participants in this study may not provide accurate information on the self-reported survey because the school report card does not support the test scores they reported. Neither does their intensity use. Using standard meta-analytic procedures, author Douglas Perry found that self-reports of media use do not exhibit convergent validity with device-logged measures of media usage (Behavioral and Social Sciences at Nature Portfolio, 2021). The results of this study imply that inaccurate and invalid self-report measures of social media use can lead to inaccurate results (Scharkow, 2016).

Although previous research focused on larger sample sizes, this study may provide evidence for studies with minimum sample sizes to focus on digital trace data (people’s time spent on their phone) instead of surveys because it is a more accurate and valid way to inform the research questions (Verbeij et al., 2021). One reason for the relatively low accuracy of retrospective survey measures may be that these estimates are prone to recall bias (Marciano & Camerini, 2020). The mean scores on the SNAIS were lower than students average test scores. This may encourage researchers to focus on a larger sample size, and more accurate and valid instruments to measure adolescents' time spent on social networks.

Limitations

This study confronted several important limitations that should be taken into consideration when interpreting the results. As discussed previously, this study focused on young adolescents, which studies have found to be at risk of developing a smartphone and social media addiction (Greenfield, 2018; Hunt et al., 2018). However, limiting the age range for this study prevents the results from being generalized to other populations. In addition, convenience sampling was the sampling technique used which is not the most effective because the estimates derived from convenience samples may lead to sampling bias.

The sample consisted of a relatively small number of just 68 participants. There were more female participants in this study than males, which may have caused a gender bias in the results. Gender bias in research could be defined as a systematically erroneous gender dependent approach related to social construct, which incorrectly regards women and men as similar/different (Ruiz-Cantero et al., 2007). An additional limitation was found with the survey responses. While Cronbach's α reflected high internal consistency for all variables, this study relied upon self-reporting for the responses to the SNAIS and it also relied upon self-reporting for test scores. When self-reported test scores were compared to school data on student performance, the absolute value of over reporting was high. Given their widespread use, it is important to specifically examine the accuracy of self-reported test scores to ascertain the extent of potential errors in estimating achievement levels (Sticca et al., 2017). This variable posed has a strong determinant in answering the research questions, and so the estimated data had potential errors impacting the results.

Recommendations for Future Research

In this study, all measures administrated were highly reliable and validated measures. Both the SNAIS and Benchmark test scores have been commonly used in prior research. This study is a worthy addition to the extant literature that quantitatively measures intense social networking use and math and science test scores because it provides a criteria for quantitative studies with potential type II error. Furthermore, there are very few studies on this topic that fail to reject the null. Future researchers may want to consider the implications and limitations of this study to increase statistical power, eliminate over/under reporting on self-reports, and recall bias. Future research may also want to consider pairing the SNAIS with digital data to add a defined usage log of measuring time spent on SNSs. This can be done by applying device or smartphone logs of social media usage to give more accuracy. Replication of this study with a larger sample, device/smartphone logs, and archival math and science test scores, would be necessary to find a significant relationship. The researcher also strongly suggests that future research attempt to recruit a diverse participant sample, enabling more analysis on different racial backgrounds, time spent on SNSs, math and science test scores, and gender differences.

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APPENDIX A

To Whom This May Concern,

I am writing to request permission to conduct a research study at X. I am currently enrolled in the Curriculum and Instruction Doctoral Program at Liberty University. The study is entitled Effect of Intense Social Media Use on At-Risk Middle School Students Test Scores in Science and Math: An Ordinal Logistic Regression Analysis.

The purpose of this research study is to examine the relationship between intense social media use and math and science test scores. To participate in the study, the student must be between the ages of 13-14 years old, spend time on one or more social media platforms, and have use of a smartphone. Each participant will receive a $10 gift card as an incentive for participation.

Participants will be asked to commit to 3-5 minutes to complete a 14 question survey. The survey results will be analyzed for the study and individual results of this study will remain absolutely confidential and anonymous. Should this study be published, there will be no identifiers.

If approval is granted, student participants will be recruited in a science/math classroom. Interested students, who volunteer to participate, will be given a recruitment letter and consent form to be signed by their parent or guardian. Participants can only complete the survey when these forms are returned. The survey will be completed in a designated classroom outside of the classroom instructional time (lunch, or after school).

If I have your permission, a response to this email is sufficient, or alternatively, kindly submit a signed letter of permission on your institution's letterhead acknowledging your consent and permission for me to conduct this survey/study at your school. If there are any questions or concerns that you may have, please contact me. Relevant materials are attached for your viewing, including the survey questions. All documents have already been verified by the IRB.

Sincerely,
Researcher and Liberty University

APPENDIX B

Research Participants Needed

Effect of Social Media on At-Risk Students Math and Science Test Scores: An Ordinal Logistic Regression Study

- *13-14 years old*
- *Spend time on one or more social media platforms*
- *Have use of a smartphone*

If you answered **yes** to either/each of the questions listed above, you may be eligible to participate in a research study.

The purpose of this research study is to examine the relationship between intense social media use and math and science test scores.

Participants will be asked to :

- *Commit to 3-5 minutes*
- *Complete an 14 question survey*

Participants will receive a $10 visa gift card at the end of participation in the study.

If you would like to participate, please provide your school ID/email on the consent form sent home or contact the researcher at the email address xx.

A hard copy or electronic consent document is provided one week before the survey.

Terry Johnson, a doctoral candidate in the School of Education at Liberty University, is conducting this study.

Please contact Terry Johnson at [redacted] or [redacted] for more information.

Liberty University IRB – 1971 University Blvd., Green Hall 2845, Lynchburg, VA 24515

APPENDIX C

Parental Consent and Student Assent

Title of the Project: Effect of Intense Social Media Use on At-Risk Middle School Students Test Scores in Science and Math: An Ordinal Logistic Regression Analysis
Principal Investigator: X, PhD Candidate, Liberty University

Invitation to be Part of a Research Study

Your child is invited to participate in a research study. Participants must be between the ages of 13-14, and in the 8th grade. They must spend time on atleast one social media platform and have use of a smartphone. Taking part in this research project is voluntary.

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

What is the study about and why are we doing it?

The purpose of the study is to investigate the relationship between intense social media use and math and science test scores in young adolescents.

What will participants be asked to do in this study?

If you agree to allow your child/student be in this study, I will ask him/her to do the following things:

1. Complete a survey asking demographic questions.
2. Complete the social media networking activity intensity (SNAIS) scale (survey) in order to measure their social media usage in their own convenient time in a classroom or other quiet setting, during a specified time period designated by the researcher that is outside of the classroom instructional time (lunch, afterschool, or at home).
3. Self-report their math and science benchmark test scores at the end of SNAIS survey.

How could participants 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 a diverse sample for this topic that helps to bridge the research gap. Knowledge from these findings can inform parents, educators, and policy makers about the relationship between intense social networking use and academics. This information can help to provide learning strategies that can improve learning outcomes in at-risk students.

What risks might participants experience from being in this study?

The risks involved in this study are minimal, which means they are equal to the risks your child would encounter in everyday life.

How will personal information be protected?

Data collected as part of this study may be shared for use in future research studies or with other researchers. If data collected from the participants is shared, any information that could identify them, if applicable, will be removed before the data is shared.

Include the following in this section:

- Participant responses will be anonymous. Participant responses will be kept confidential through the use of pseudonyms/codes.
- Data will be stored on a password-locked computer and may be used in future presentations. After three years, all electronic records will be deleted.

How will participants be compensated for being part of the study?

Participants will be compensated for participating in this study. Each participant will receive a $10 gift card only if they complete the study and answer all survey questions.

What conflicts of interest exist in this study?

The researcher serves as a teacher at the school. To limit potential or perceived conflicts the researcher will not use own students. This disclosure is made so that you can decide if this relationship will affect your willingness to allow your child to participate in this study. No action will be taken against an individual based on her or his decision to allow his or her child to participate in this study.

Is study participation voluntary?

Participation in this study is voluntary. Your decision whether or not to allow your child to participate will not affect their current or future relations with Liberty University. If you decide to allow your child to participate, he/she is free to not answer any question or withdraw at any time without affecting those relationships.

What should be done if a participant wishes to withdraw from the study?

If you choose to withdraw your child from the study or your child chooses to withdraw, please have them exit the survey and close their internet browser—OR—inform the researcher that your child wishes to discontinue his/her participation, and your child should not submit the study materials. Your child’s 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 X. You may ask any questions you have now. If you have questions later, **you are encouraged** to contact her at X@liberty.edu. You may also contact the researcher's faculty sponsor, X, at X@liberty.edu.

Whom do you contact if you have questions about 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 Institutional Review Board, 1971 University Blvd., Green Hall Ste. 2845, Lynchburg, VA 24515 or email at 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/Opt-Out]

By signing this document, you are agreeing to allow your child to be in this study. Make sure you understand what the study is about before you sign. You will be given a copy of this document for your records. The researcher will keep a copy with the study records. If you have any questions about the study after you sign this document, you can contact the study team using the information provided above.

I have read and understood the above information. I have asked questions and have received answers. I consent to allow my child to participate in the study.

____

Printed Child's/Student's Name

____

Parent's Signature Date

____ ________________

Minor's Signature Date Email

APPENDIX D

The demographic survey includes questions to ascertain the participant's gender, age, race, as well as whether or not they qualified for free or reduced lunch.

APPENDIX E

SNAIS SCALE

How often have you performed the following online social networking activities in the last month?

Social Function 1. Sent messages to friends on message board.

2. Chatted with friends via instant messaging function.

3. Replied to comments made by social networking friends.

4. Commented on friends' status, logs, and photos.

5. Shared/Forwarded content.

6. Browsed others' logs/photos/statuses/albums.

7. Updated self-status.

8. Posted photos/videos on personal web profile.

9. Wrote logs/weibo.

10. Decorated personal web profile.(changed image/contact information/privacy setting)

Entertainment Function Use Intensity

11. Surfed entertainment/current news.

12. Watched video/listened to music.

13. Played games/applications.

14. Bought/gave virtual goods. (e.g. birthday gifts)

Note. Items are on a 5-point scale: 0 (never), 1 (few), 2 (sometimes), 3 (often) and 4 (always).

Self-Reported Test Scores

15. What score did you receive on your most recent benchmark math test?

16. What score did you receive on your most recent benchmark science test?

APPENDIX F

Application #:
2021-2022 Application for Free and Reduced Price School Meals
Complete one application per household. Please type or use a pen (not a pencil).

Available online at: https://irvington.k12.nj.us/food-service-programs/

STEP 1 List ALL Household Members who are infants, children, and students up to and including Grade 12 (if more spaces are required for additional names, attach another sheet of paper)

Definition of **Household Member**: "Anyone who is living with you and shares income and expenses, even if not related."

Children in **Foster care** and children who meet the definition of **Homeless, Migrant** or **Runaway** are eligible for free meals. Read **How to Apply for Free and Reduced Price School Meals** for more information.

Child's First Name	MI	Child's Last Name [press spacebar to advance]	School Name (Abbr.)	Grade	Student attends this school district? Yes	No	Foster Child	Migrant Worker, Homeless, Runaway

Check all that apply

STEP 2 Do any Household Members (including you) currently participate in one or more of the following assistance programs: SNAP, TANF, or FDPIR? YES ☐ NO ☐

If you answered NO > Complete STEP 3. **If you answered YES** > Write a case number here then go to STEP 4 (Do not complete STEP 3) **Case Number:**

Write only one case number in this space.

STEP 3 Report Income for ALL Household Members (Skip this step if you answered 'Yes' to STEP 2)

Are you unsure what income to include here?

Flip the page and review the charts titled "Sources of Income" for more information.

The "Sources of Income for Children" chart will help you with the Child Income section.

The "Sources of Income for Adults" chart will help you with the All Adult Household Members section.

A. Child Income
Sometimes children in the household earn or receive income. Please include the TOTAL income received by all Household Members listed in STEP 1 here.

Child income $ ___ How often? Weekly / Bi-Weekly / 2x Month / Monthly

B. All Adult Household Members (including yourself)
List all Household Members not listed in STEP 1 (including yourself) even if they do not receive income. For each Household Member listed, if they do receive income, report total gross income (before taxes) for each source in whole dollars (no cents) only. If they do not receive income from any source, write '0'. If you enter '0' or leave any fields blank, you are certifying (promising) that there is no income to report.

Name of Adult Household Members (First and Last)	Earnings from Work	How often? Weekly / Bi-Weekly / 2x Month / Monthly	Public Assistance/ Child Support/Alimony	How often? Weekly / Bi-Weekly / 2x Month / Monthly	Pensions/Retirement/ All Other Income	How often? Weekly / Bi-Weekly / 2x Month / Monthly
	$		$		$	
	$		$		$	
	$		$		$	
	$		$		$	
	$		$		$	

Total Household Members (Children and Adults)

Last Four Digits of Social Security Number (SSN) of Primary Wage Earner or Other Adult Household Member X X X X X

Check if no SSN

STEP 4 Contact information and adult signature. **Mail Completed Form To:**

"I certify (promise) that all information on this application is true and that all income is reported. I understand that this information is given in connection with the receipt of Federal funds, and that school officials may verify (check) the information. I am aware that if I purposely give false information, my children may lose meal benefits, and I may be prosecuted under applicable State and Federal laws."

Street Address (if available) Apt # City State Zip Daytime Phone and Email (optional)

Printed name of adult signing the form Signature of adult Today's date

INSTRUCTIONS Sources of Income

Sources of Income for Children

Sources of Child Income	Example(s)
- Earnings from work	- A child has a regular full or part-time job where they earn a salary or wages
- Social Security - Disability Payments - Survivor's Benefits	- A child is blind or disabled and receives Social Security benefits - A Parent is disabled, retired, or deceased, and their child receives Social Security benefits
-Income from person outside the household	- A friend or extended family member regularly gives a child spending money
-Income from any other source	- A child receives regular income from a private pension fund, annuity, or trust

Sources of Income for Adults

Earnings from Work	Public Assistance / Alimony / Child Support	Pensions / Retirement / All Other Income
- Salary, wages, cash bonuses - Net income from self-employment (farm or business) If you are in the U.S. Military: - Basic pay and cash bonuses (do NOT include combat pay, FSSA or privatized housing allowances) - Allowances for off-base housing, food and clothing	- Unemployment benefits - Worker's compensation - Supplemental Security Income (SSI) - Cash assistance from State or local government - Alimony payments - Child support payments - Veteran's benefits - Strike benefits	- Social Security (including railroad retirement and black lung benefits) - Private pensions or disability benefits - Regular income from trusts or estates - Annuities - Investment income - Earned interest - Rental income - Regular cash payments from outside household

OPTIONAL Children's Racial and Ethnic Identities

We are required to ask for information about your children's race and ethnicity. This information is important and helps to make sure we are fully serving our community. Responding to this section is optional and does not affect your children's eligibility for free or reduced price meals.

Ethnicity (check one): Hispanic or Latino ☐ Not Hispanic or Latino ☐
Race (check one or more): American Indian or Alaskan Native ☐ Asian ☐ Black or African American ☐ Native Hawaiian or Other Pacific Islander ☐ White ☐

The **Richard B. Russell National School Lunch Act** requires the information on this application. You do not have to give the information, but if you do not, we cannot approve your child for free or reduced price meals. You must include the last four digits of the social security number of the adult household member who signs the application. The last four digits of the social security number is not required when you apply on behalf of a foster child or you list a Supplemental Nutrition Assistance Program (SNAP), Temporary Assistance for Needy Families (TANF) Program or Food Distribution Program on Indian Reservations (FDPIR) case number or other FDPIR identifier for your child or when you indicate that the adult household member signing the application does not have a social security number. We will use your information to determine if your child is eligible for free or reduced price meals, and for administration and enforcement of the lunch and breakfast programs. We MAY share your eligibility information with education, health, and nutrition programs to help them evaluate, fund, or determine benefits for their programs, auditors for program reviews, and law enforcement officials to help them look into violations of program rules.

In accordance with Federal civil rights law and U.S. Department of Agriculture (USDA) civil rights regulations and policies, the USDA, its Agencies, offices, and employees, and institutions participating in or administering USDA programs are prohibited from discriminating based on race, color, national origin, sex, disability, age, or reprisal or retaliation for prior civil rights activity in any program or activity conducted or funded by USDA.

Persons with disabilities who require alternative means of communication for program information (e.g. Braille, large print, audiotape, American Sign Language, etc.), should contact the Agency (State or local) where they applied for benefits. Individuals who are deaf, hard of hearing or have speech disabilities may contact USDA through the Federal Relay Service at (800) 877-8339. Additionally, program information may be made available in languages other than English.

To file a program complaint of discrimination, complete the USDA Program Discrimination Complaint Form, (AD-3027) found online at: http://www.ascr.usda.gov/complaint_filing_cust.html, and at any USDA office, or write a letter addressed to USDA and provide in the letter all of the information requested in the form. To request a copy of the complaint form, call (866) 632-9992. Submit your completed form or letter to USDA by:

mail civil rights complaints **only** to: U.S. Department of Agriculture
Office of the Assistant Secretary for Civil Rights
1400 Independence Avenue, SW
Washington, D.C. 20250-9410

fax: (202) 690-7442; or
email: program.intake@usda.gov.

This institution is an equal opportunity provider.

Do not fill out For School Use Only

Annual Income Conversion: Weekly x 52, Every 2 Weeks x 26, Twice a Month x 24, Monthly x 12

Total Income How often? Weekly / Bi-Weekly / 2x Month / Monthly / Annual **Household Size** **Categorical Eligibility** ☐ Eligibility: Free / Reduced / Denied

Determining Official's Signature Date **Confirming Official's Signature** Date **Verifying Official's Signature** Date